INTEGRATED STRATEGIC, TACTICAL AND OPERATIONAL PLANNING OF FOREST-BASED BIOMASS SUPPLY CHAINS FOR ENERGY AND FUEL PRODUCTION - A HYBRID OPTIMIZATION SIMULATION APPROACH

by

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Abstract

Biomass has emerged as an attractive renewable source of energy to shift away from fossil fuels. However, the high cost of biomass feedstock and variations, such as those in biomass supply and demand, impact the competitiveness of biomass and restrict bioenergy and biofuel developments. Therefore, supply chain planning is essential in improving the efficiency of biomass supply chains.

In the literature, supply chain planning often has been carried out at strategic, tactical, and operational levels hierarchically by developing distinct models. Hierarchical planning may result in inconsistent and even infeasible solutions of higher planning levels at the lower levels because the details and variations at the lower levels are not considered at the higher levels. Hence, integrating the three different planning levels, while capturing the variations at the lower planning levels, could assure that plans from higher levels (e.g., strategic) are attainable at lower planning levels (tactical and operational). However, an integrated optimization model could require an enormous computational effort for solving. Therefore, proper solution approaches that can overcome this problem should be used. The main goal of this dissertation is to develop an integrated strategic, tactical, and operational planning model considering variations and details of lower planning levels, and employ a suitable solution approach to solve it.

Herein, first, an optimization model that integrates the strategic and tactical decisions of forest-based biomass supply chains is developed to optimize the design of the supply chain considering variations at the tactical level. Then, three common decision rules, representing optimistic, moderate pessimistic, and pessimistic perspectives, are used to optimize the design of the supply chain considering the decision maker’s perspective towards risk. Next, a discrete event simulation model is developed to incorporate the operational level variations and its aspects. Finally, a hybrid scheme is proposed in which a linkage between the optimization and the simulation models is constructed to integrate different planning levels while incorporating variations at tactical and operational levels. The hybrid model is applied to a case study. The results of this research indicate that ignoring the tactical and operational level variations could result in sub-optimal and even infeasible solutions.
Lay summary

Biomass is an attractive renewable source of energy to shift away from fossil fuels. However, several issues, including seasonality in biomass availability, dispersed geographic location, and low bulk density make its supply chain complex and contribute to its high cost compared with other fuels. In order to improve its competitiveness compared with that of fossil fuels, in several studies decision models are developed for designing efficient supply chains addressing the complexities. However, less attention has been paid to variations in biomass supply chains. In this research, the objective is to determine the location, type, and size of conversion facilities for producing bioenergy and biofuels to achieve the maximum profit while addressing variations in biomass supply chains. The results of this study indicate that ignoring variations in biomass supply and demand could result in considerable profit losses if those solutions are implemented.
Preface

All the work presented in this dissertation was carried out by the author, Shaghaygh Akhtari, during her Ph.D. program, under the supervision of Dr. Taraneh Sowlati, at the Industrial Engineering Research Group of the University of British Columbia, Vancouver, BC.

Parts of this work is presented in the following publications.

- A version of Chapter 2 is published [Akhtari, S., & Sowlati, T. (2015). Hybrid simulation optimization approach to tackle supply chain complexities: A review with a focus on forest products supply chains. Journal of Science & Technology for forest products and processes, 5(5), 26-39]. I was responsible for defining the topic, searching the literature, synthesizing the information, as well as writing the manuscript. Sowlati, T. was the supervisory author on this publication and was involved throughout the review and manuscript composition.

- A version of Chapter 3 is published [Akhtari, S., Sowlati, T., & Griess, V. C. (2018). Integrated strategic and tactical optimization of forest-based biomass supply chains to consider medium-term supply and demand variations. Applied Energy, 213, 626-638]. I was the main contributor of this paper. I defined the research problem, collected the data, developed the model and solved it, and composed the manuscript. Sowlati, T. was the supervisory author on this publication and provided the advising support in defining the research problem and objective, data gathering process, developing, validating and applying the models, as well as editorial guidance on the written work derived from Chapter 3. Griess, V. C. contributed to manuscript edits.

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developing, validating and applying the model, as well as editorial guidance on the written work derived from Chapter 5. Siller, D. was involved in initial stages of building the model and Roeser, D. contributed to data collection.

The following parts of this work are in preparation for submission to refereed journals.

- A version of Chapter 6 will be submitted. Integrated strategic, tactical, and operational planning of a forest-based biomass supply chain - A Hybrid optimization simulation scheme.
- A version of Chapter 3 will be submitted. Integrated strategic and tactical optimization of a forest-based biomass supply chain considering uncertainties – A robust optimization model.
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To my family
Chapter 1. Introduction

1.1 Background

The supply of sustainable energy is one of the most serious challenges that mankind will have to confront over the coming decades, particularly because of the need to address climate change (Bauen, Berndes, Junginger, Londo, & Vuille, 2009). Biomass, as a clean, renewable, and domestic source of energy has become of enormous importance in the fight against climate change (Bauen et al., 2009). According to the International Energy Agency (2017), biomass currently constitutes the largest share in the global renewable energy supply (Figure 1.1); yet, there is a significant potential to expand the use of biomass to supply future energy demand in a sustainable manner (International Energy Agency, 2017).

![Figure 1.1: Share of bioenergy in the world primary energy mix](image)


1 Other refers to the sources not included elsewhere, such as non-renewable wastes and fuel cells

2 Other includes solar, wind, tide and geothermal energy

The further expansion of the biomass share in meeting the global energy demand can play a significant role in environmental and socio-economic improvements, particularly in rural communities (Bauen et al., 2009). From the environmental perspective, the use of biomass can reduce carbon emissions and the threats of acid rain (Jacobson & Ciolkosz, 2013). Additionally, exploiting biomass for energy is an opportunity for better use of natural resources and can enhance the waste disposal problems (Bauen et al., 2009; Jacobson & Ciolkosz, 2013). From the socio-economic point of view, replacing imported fossil fuels with locally generated biomass improves energy security and provides opportunities for
economic and social development by creating long term employment opportunities (Bauen et al., 2009; Jacobson & Ciołkosz, 2013).

Despite its potential contributions to socio-economic development and emission reductions, investment in bioenergy and biofuel projects still faces many challenges. Lack of reliable supply and the high cost of the biomass supply chain are one of the main barriers to bioenergy and biofuel developments (Gold & Seuring, 2011). Moreover, bioenergy and biofuel projects require high capital investment (Sims, 2013). There is considerable uncertainty around these investments. Uncertainties in biomass availability, quality, and procurement costs are some examples. Furthermore, since the bioenergy and biofuel industry is relatively new, there is a lack of information about historical financial performance; this adds additional uncertainty for investors (Hampl, 2012). Because of these factors, biomass supply chain planning is imperative in enhancing the profitability of bioenergy production (Gunasekaran, Patel, & McGaughey, 2004).

Biomass supply chain planning can be carried out at strategic, tactical, and operational levels (Awudu & Zhang, 2012; De Meyer, Cattrysse, Rasinmäki, & Van Orshoven, 2014; Yue, You, & Snyder, 2014). The strategic plans determine the resource requirements such as number, location and capacity of production and storage facilities, as well as the flow of material through the strategic network, whereas tactical and operational level plans are concerned with efficient utilization of resources (Awudu & Zhang, 2012; De Meyer et al., 2014; Yue et al., 2014).

Numerous mathematical programming models have been developed for the strategic planning of bioenergy and biofuel supply chains (e.g. Cambero, Sowlati, Marinescu, & Röser, 2015; Chinese & Meneghetti, 2005; de Jong et al., 2017; Elia, Bian, Xia, & Floudas, 2011; Feng, D’Amours, LeBel, & Nourelfath, 2010; Freppaz et al., 2004; Frombo, Minciardi, Robba, & Sacile, 2009; Huang, Chen, & Fan, 2010; Jonker et al., 2016; Kim, Realff, Lee, Whittaker, & Furtner, 2011; Leduc, Lundgren, Franklin, & Dotzauer, 2010; Leduc, Starfelt, et al., 2010; Nagel, 2000; Parker et al., 2010; Rauch & Gronalt, 2010; Tittmann, Parker, Hart, & Jenkins, 2010). These studies addressed the optimal design of the supply chains which involved determining the optimal location, size, and type of bioconversion, storage, and product upgrading facilities.

For a given supply chain design, a number of tactical models have been developed to address decisions related to medium-term production planning, inventory control and logistics management (e.g., Akhtari, Sowlati, & Day, 2014a; Eriksson & Björheden, 1989; Gunnarsson, Rönqvist, & Lundgren, 2004; Kanzian, Holzleitner, Stampfer, Ashton, & others, 2009; Shabani & Sowlati, 2013), while operational level models have been developed for short-term planning, such as vehicle routing and scheduling (e.g., Han & Murphy, 2012; Malladi, Quirion-Blais, & Sowlati, 2018).
Often, separate optimization models have been developed for strategic, tactical, and operational plans; integrating the three planning levels has been overlooked. Integrating different planning levels is required to assure that plans from higher levels (e.g. strategic) are attainable at lower planning levels (tactical and operational). When planning is divided into different levels, using solutions from one level may result in inconsistent and even infeasible solutions at other planning levels (Andersson, 2005). This happens because each lower planning level includes variations that are not accounted for at higher levels. In order to avoid infeasibility and inconsistency issues, it is important to integrate the three planning levels. However, constructing and solving integrated problems is challenging mainly because of the large number of decision variables and constraints that are needed for consistency among the overlapping decisions in various planning levels. For instance, Memişoğlu and Üster (2015) developed an integrated strategic and tactical level optimization model in which the number, size, and location of collection and bioethanol facilities were determined at the strategic level and logistics management and inventory planning decisions were defined at the tactical level. However, their model was difficult\(^1\) to solve using standard solvers; therefore, they had to use decomposition\(^2\) to obtain a solution.

Integrated supply chain planning problems become further complicated in the presence of variations at the operational level (Shapiro, 2010), or when supply chain networks with complex structures, e.g. multi-facility, multi-product, multi-period networks, are considered. In these cases, stochastic programming and robust optimization, which are conventional techniques that are commonly used in biomass supply chain optimization to incorporate the variations in planning, may not be efficient to solve integrated models. This is because the size and complexity of the problems that stochastic and robust optimization problems can handle are limited (Parsons, 2001). Stochastic and robust optimization were used for addressing uncertainties in biomass supply chain planning (Chen & Fan, 2012; Kim, Realff, & Lee, 2011a; Shabani & Sowlati, 2016; Shabani, Sowlati, Ouhimmou, & Rönqvist, 2014; Svensson & Berntsson, 2011; Svensson, Strömberg, & Patriksson, 2011; Tay, Ng, & Tan, 2013; Tong, You, & Rong, 2014; Zamar, Gopaluni, & Sokhansanj, 2017; Zamar, Gopaluni, Sokhansanj, & Newlands, 2017). A number of these studies focused on uncertainty in biomass availability and product demand (Chen & Fan, 2012; Shabani et al., 2014; Tay et al., 2013; Tong et al., 2014). Several publications dealt with uncertainty in biomass supply, demand, prices, conversion

\(^1\)A difficult optimization problem is defined as a problem which cannot be solved to optimality or any guaranteed bound by any standard solver within a reasonable time limit (Kallrath, 2009).

\(^2\)Decomposition is a general approach for solving a problem by breaking it up into smaller ones and solving each of the smaller models separately, either in parallel or sequentially (Boyd, Xiao, Mutapcic, & Mattingley, 2015).
yields, carbon tax and emission reduction policies (Svensson & Berntsson, 2011; Svensson et al., 2011) and biomass quality (Shabani & Sowlati, 2016; Zamar, Gopaluni, & Sokhansanj, 2017; Zamar, Gopaluni, Sokhansanj, et al., 2017). However, these problems were not difficult problems and they could be solved using standard solvers within a reasonable time. However, there is a need for solution approaches that can overcome the challenges of incorporating several sources of variations when integrating different planning levels.

To overcome some of the challenges related to incorporating uncertainties, several authors used simulation to model stochastic and complex forest logistics operations taking into account uncertainty in biomass supply and demand as well as quality, machine interactions and interdependencies among various stages of the supply chain (e.g., Asikainen, 2010; Karttunen et al., 2012; Mahmoudi, Sowlati, & Sokhansanj, 2009; Mobini et al., 2014; Mobini, Sowlati, & Sokhansanj, 2011, 2013; Sessions, Zamora, Murphy, & Boston, 2013; Talbot & Suadicani, 2005; Zhang, Osmani, Awudu, & Gonela, 2013). Despite the advantages of simulation modeling in incorporating uncertainties and their ability to capture the behavior of complex and detailed supply chains, they lack the capability of providing optimal solutions (Arisha & Abo-Hamad, 2010). Therefore, model developers need to be equipped with comprehensive solution tools to overcome the challenges in the supply chain planning. The hybrid simulation optimization approach, which involves developing individual simulation and optimization models for problem-solving, is a potential approach to overcome the modeling complexities of supply chain planning. In this approach, the simulation component can include the stochastic parameters and provide a better representation of a complex system, while the optimization component provides optimum or near optimum solutions (Kulkarni & Venkateswaran, 2014).

Considering the time horizon, scale, complexity, and high degrees of variation in biomass supply chain planning, the use of hybrid simulation optimization models can provide the possibility to increase the reliability of the results and improve the possibility of achieving optimal results (Mardan & Klahr, 2012). In biomass supply chain planning, only Ebadian, Sowlati, Sokhansanj, Smith, and Stumborg (2014) used a hybrid optimization simulation approach to solve their integrated tactical and operational level problem under uncertainty. In this study, the tactical decisions including the amount of biomass to transport from farms and storage sites to a bioethanol plant were defined in a deterministic optimization model. Then, a discrete event simulation model was developed to consider the uncertainty in biomass availability, product demand, machine availability, and weather conditions in finding the optimal configuration of a bioethanol supply chain. This model only considered minimizing the annual delivery cost of biomass to the gate of the bioethanol facility. Moreover, Ebadian et al. (2014) considered agricultural biomass for ethanol production in a facility in a defined location with a given
capacity. To best of my knowledge, no previous study applied the hybrid optimization-simulation approach to address uncertainty in forest-based biomass supply chain planning integrating strategic, tactical, and operational level aspects of the supply chain.

1.2 Research objectives

The overall goal of this work is to develop an integrated strategic, tactical, and operational planning model considering variations and details of lower planning levels including:

- The dynamics of the supply chain at the tactical level, i.e., seasonality in biomass availability, variations in product demand, and losses during preprocessing and storage of biomass
- The variations and operating constraints at the operational level, i.e., weather condition, machine interactions, and interdependencies among different stages of the supply chain, and

employ a suitable solution approach to solve it.

This overall goal is achieved through the progressive development of a hybrid optimization-simulation approach in three stages as follows:

1) Develop and solve an optimization model that integrates the strategic and tactical level decisions. This model defines the type, location, and size of conversion facilities at the strategic level, the flow of biomass between biomass sources and conversion facilities, and the flow of products between conversion facilities and end-users at the tactical level. Additionally, optimizing the design of the supply chain considering the decision maker’s viewpoint towards risk is addressed at this stage.

2) Build and run a discrete event simulation model to evaluate the proposed supply chain design taking into account operational level aspects. Specifically, the impact of inventory control and management on the total cost, emissions and demand fulfillment of the design is evaluated.

3) Combine the optimization and simulation models to obtain an overall supply chain design that is feasible at tactical and operational levels.

This hybrid model is applied to a case study, which is described in the following section.

1.3 Case study

British Columbia (BC) has a large forest industry with an annual harvest level of 67,970,000 cubic meters and a harvested area of 192,615 hectares in 2015 (Natural Resources Canada, 2018a). As a result of logging and milling activities, a significant amount of wood waste including non-merchantable logs, roadside waste, and sawmill residues is generated annually in the province (Bradley, 2007). A quantity
of these residues is used within the forest industry in pulp, pellet, and particle board facilities and in the agricultural sector for bedding, soil manufacture, and greenhouses (Bradley, 2007). The remainder of the residues is disposed of by landfilling and/or open burning (Industrial Forestry Service Ltd., 2010). To avoid the negative impacts of landfilling and open-burning on the air quality, innovative uses, such as using the waste for energy, have been developed recently (Industrial Forestry Service Ltd., 2010). BC Hydro forecasted a potential bioenergy capacity of 1,360 MW estimated for a 13-year period of 2013-2024 in BC (Industrial Forestry Service Ltd., 2010). This capacity can be used to fulfill 24% of the annual energy demand in BC through bioenergy (heat and/or power generation) and biofuels (solid or liquid fuels) production (Renney, 2012). However, forest biomass is utilized to generate only 1% of the province’s annual demand (Renney, 2012).

In this dissertation, a case study in British Columbia (BC), Canada, is considered. This region includes several features which make it a suitable case study for this research as explained below.

Characterized by extensive lodgepole pine (Pinus Contorta) forests, British Columbia is affected by a recent massive mountain pine beetle (Dendroctonus Ponderosae) infestation that has devastated approximately 731 million m³ (54%) supply of its merchantable pine (Ministry of Forests, Lands, Natural Resource Operations & Rural Development, 2018). In addition to the decreased supply of timber following the beetle infestation, eroding log quality exhibited by the mountain pine beetle (MPB) has imposed challenges in lumber recovery and processing costs and resulted in production reduction at sawmills, mill curtailment and/or closure (Stickney & Doucet, 2007). Since many communities in BC are highly dependent on the forest industry activities (MNP LLP, 2015), the closure of the wood processing facilities has left many people unemployed (SIBAC, 2011). BC includes several communities that have limited or no access to electricity from the provincial grid. These communities depend on expensive and pollutant electricity generated by diesel generators. In addition to the high cost of electricity, these communities are concerned with environmental and social issues (e.g., air and noise pollutions) related to the transportation and use of diesel.

Investing in biomass conversion facilities to transform harvesting and mill residues into heat and/or power could help meet the energy demand of sawmills and the nearby communities at a lower price than the current ones. In addition to economic benefits, producing bioenergy and also other bioproducts, such as pellets and bio-oil, could contribute to the revitalization of the mills by generating new streams of income through access to new bioproduct markets. Bioenergy and biofuel production could also contribute to the well-being of the communities through new employment opportunities for harvesting/collecting, processing, and transporting of biomass, as well as building and operating the facilities (MNP LLP, 2015).
In this case study, different utilization paths for available residues are examined for the production of energy in a region in BC, Canada. The three main mill centers in three major communities in this region are considered as the candidate locations for new bioenergy and biofuel conversion facilities. Henceforth, these locations will be referred to as location A, B, and C.

Four biomass types are available and considered: harvesting residues including tree tops and branches, and non-merchantable MPB-killed logs from 1592 aggregated forest cut-blocks, as well as wood chips and hog fuel from local sawmills. Figure 1.2 and Figure 1.3 illustrate the average availability of harvesting residues and sawmill residues, respectively.

**Figure 1.2:** Average annual availability of residues from forest cut-blocks in the case study over time (Derived from the data provided by FPInnovations (Friesen, 2012))

**Figure 1.3:** Average annual availability of residues from sawmills in the case study (Derived from Marinescu 2012; Marinescu 2013; Akhtari, Sowlati & Day 2014b)
The potential conversion technologies for bioenergy and biofuel consist of 41 combinations of different technologies and sizes that can be established in the three candidate locations. Table 1-1 lists the candidate technology alternatives for bioenergy and biofuel production.

<table>
<thead>
<tr>
<th>Product</th>
<th>Technology alternative</th>
<th>Capacities a</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heat only</td>
<td>Biomass stoker boiler</td>
<td>0.5,1,2,3,5 MW</td>
</tr>
<tr>
<td>Power only/</td>
<td>Biomass boiler + steam turbine</td>
<td>0.5,1,2,3,5 MW</td>
</tr>
<tr>
<td>Combined heat</td>
<td>Biomass gasifier + internal combustion engine</td>
<td>0.5,1,2,3,5 MW</td>
</tr>
<tr>
<td>and power</td>
<td>Biomass oil heater + organic Rankine cycle</td>
<td>0.5,1,2,3,5 MW</td>
</tr>
<tr>
<td>Wood pellet</td>
<td>Pelletizing</td>
<td>15000, 30000, 45000 tonnes per year</td>
</tr>
<tr>
<td>Bio-oil</td>
<td>Fast pyrolysis</td>
<td>200, 400, 600 Odmt biomass per day</td>
</tr>
</tbody>
</table>

a The capacity of the pyrolysis facility is expressed based on its biomass input capacity. The capacity for the rest of the facilities is based on their output products.

The bioenergy generation technologies were proposed by FPInnovations based on the results of previous feasibility studies (Marinescu, 2012, 2013). Biofuel conversion technologies were selected based on the results of the Bio-Pathways Project (FPAC, 2011), in which fast pyrolysis and pelletizing were identified as the most promising technologies among a variety of traditional and emerging ones for the utilization of forest-based residues in British Columbia.

It is worth noting that the work in this dissertation is an academic research and its main objective is to gain a deep understanding of the subject and add to the body of knowledge. Therefore, the results of this study are not intended to recommend any specific investment by government or private investors in the studied region.

1.4 Outline of the dissertation

In addition to the current chapter, this dissertation includes the following chapters:

Chapter 2 provides a review of the approaches and methodologies used for managing and planning biomass and biofuel supply chains.

In Chapter 3, a deterministic mixed integer linear programming (MILP) model that integrates the strategic and tactical decision-making levels is developed to maximize the net present value (NPV) of investment in bioenergy and biofuel production. The model is applied to the case study that is described in Section 1.3. The results are presented and analyzed.
In Chapter 4, a series of sensitivity analyses are performed to evaluate the impact of variations in the model parameters on the optimal solution that is obtained from the integrated model in Chapter 3. Then, using the principles of decision analysis under uncertainty, the impact of the decision maker’s viewpoint on deciding about investing in bioenergy and biofuel production is evaluated. In this evaluation, uncertain future conditions resulting from changes in biomass availability and procurement cost, bioproduct selling prices, and conventional energy prices are taken into account. Results are analyzed considering optimistic, opportunistic, and pessimistic decision making viewpoints towards risk.

A discrete event simulation model is developed in Chapter 5 for quantifying the demand fulfillment, greenhouse gas (GHG) emissions, and total logistics costs of the supply chain design obtained in Chapter 3 at the operational level under uncertainties. This model includes the upstream logistics of the supply chain and inventory management at the conversion facilities.

Chapter 6 presents the development of an iterative hybrid optimization simulation approach, in which the integrated strategic and tactical optimization model developed in Chapter 3 and the discrete event simulation model developed in Chapter 5 are integrated together. In this hybrid approach, the optimization improves the optimal solution based on the feedback that it receives from the simulation model with respect to the performance of the solution.

Finally, Chapter 7 presents a summary of this dissertation including the final conclusions, strengths and limitations of the work, and some ideas for future research.
Chapter 2. Literature review

2.1 Synopsis

Supply chain planning can play a key role in ensuring that biomass is cost-competitive with fossil fuels. However, some characteristics of biomass complicate biomass supply chain planning and create the need for decision support models that can solve complex problems and improve the decision-making process. In this chapter, the biomass supply chain is defined, and then the important factors that should be addressed in biomass supply chain planning are described. The alternative operations research methods that have been used for supply chain planning are reviewed under three main categories: optimization models, simulation models, and hybrid optimization-simulation models. Finally, the features and limitation of each group are discussed.

2.2 Forest-based biomass supply chain management

2.2.1 Forest-based biomass supply chains for bioenergy and biofuel

A supply chain is broadly defined as a network of suppliers, producers, distributors, and end users, which are known as supply chain entities (Simchi-Levi, Kaminsky, Simchi-Levi, & Shankar, 2008). It includes all the processes that are involved in raw material procurement, transportation, storage, the transformation of raw material into a final product, as well as product storage and distribution to end users in corresponding markets (Simchi-Levi et al., 2008).

Figure 2.1 illustrates the general structure of a forest-based biomass supply chain. As seen in this figure, a forest-based biomass supply chain consists of biomass supply sources (i.e., forest areas, sawmills, pulp mill, and other wood processing facilities), from which biomass is procured, conversion facilities, where biomass is transformed into useful products (e.g., energy, fuel, and chemicals, as well as end-users, who ultimately use the bioproducts (Sowlati, 2016)).

Forest-based biomass supply chains include many activities that can be classified into upstream, midstream, and downstream categories (De Meyer et al., 2014). Upstream supply chain encompasses the activities prior to conversion (De Meyer et al., 2014). First, biomass should be collected from biomass supply sources. Most often, biomass cannot be converted into products in its original form; preprocessing is required to reduce its size through chipping/grinding and to decrease its moisture content through drying to acceptable values by the conversion technologies (An, Wilhelm, & Searcy, 2011). In order to match demand and supply and avoid any interruption in production, biomass storage, which could be in ambient air or under a covered area, is required (Rentizelas, Tolis, & Tatsiopoulos, 2009). Biomass preprocessing and storage can take place at the source locations, at the conversion facility, or in an intermediate location (Rentizelas et al., 2009). Then, depending on the location of
preprocessing and storage, biomass is transported directly from supply sources or indirectly via storage facilities to conversion facilities, either before or after preprocessing (Rentizelas et al., 2009).

![Figure 2.1: General structure of a forest-based biomass supply chain](image)

The midstream segment focuses on the internal operations of conversion facilities (De Meyer et al., 2014), where preprocessed residues are transformed into useful energy products, i.e. heat, electricity, or combined heat and power (CHP), processed into biofuels such as wood pellets, pyrolysis bio-oil, or biochemical products, such as solvents (Bender, 2000; Demirbas, 2006). Finally, through the downstream chain, the products are distributed to their end-users directly from conversion facilities or indirectly via storage facilities (De Meyer et al., 2014).

### 2.2.2 Forest-based biomass supply chain planning

Biomass supply chain planning is concerned with the integration and coordination of various activities from procurement of raw material to the distribution of final products to customers (Simchi-Levi et al., 2008). Traditionally, supply chain planning is divided into a hierarchy of decision-making phases with respect to planning horizon and the type of decisions to address (Mula, Peidro, Díaz-Madroñero, & Vicens, 2010). The strategic level is the highest level of the hierarchy which addresses the long term and capital intensive decisions related to the design of the supply chain (Awudu & Zhang, 2012; Iakovou, Karagiannidis, Vlachos, Toka, & Malamakis, 2010). These decisions cannot be altered once they are implemented without major costs (De Meyer et al., 2014). At this level, locations, where facilities (preprocessing, storage, conversion, and/or upgrading facilities) can be opened are prescribed; the technology to employ at each location and the operating capacities are determined (Awudu &
Zhang, 2012; Iakovou et al., 2010). Simultaneously, decisions pertaining to biomass sourcing (e.g., type of biomass to procure and allocation of biomass between the supply chain entities) may be tackled (Awudu & Zhang, 2012; Iakovou et al., 2010). Therefore, the strategic level establishes the design of supply chain network and provides the environment in which tactical and operational levels should perform (Schmidt & Wilhelm, 2000). Over this long planning horizon, a great deal of uncertainty exists (Schmidt & Wilhelm, 2000). At the tactical level, the amounts of biomass and products that are transported within the supply chain network are quantified and the level of inventory to keep in the storage units is defined over medium-term (monthly) (Awudu & Zhang, 2012; Iakovou et al., 2010). Compared with the strategic level, the tactical level entails less uncertainty because of its shorter planning horizon (Schmidt & Wilhelm, 2000). Finally, the operational level, which is constrained by tactical plans, deals with very short-term planning of daily activities, such as vehicle routing and scheduling of the operations, to assure in-time distribution of the products to the end-users (Awudu & Zhang, 2012; Iakovou et al., 2010). When planning, several technical and economic aspects related to upstream, midstream, and downstream activities should be considered.

- **Important considerations in the upstream supply chain**

Biomass feedstock can impact the economic viability of forest-based biomass supply chains in several ways. First, biomass availability restricts the operating capacity of bioenergy and biofuel systems (Allen, Browne, Hunter, Boyd, & Palmer, 1998). Its scattered availability impacts the transportation costs (Kumar, Cameron, & Flynn, 2003; Mitchell, Bridgwater, Stevens, Toft, & Watters, 1995); for biomass with higher rates of availability per area, fewer truck movements are required which can considerably decrease transportation costs. Moreover, seasonal variations in forest-based biomass availability create the need for storage (Rentizelas et al., 2009). Although biomass storage ensures a continuous feedstock supply, it increases the storage and handling costs (Rentizelas et al., 2009).

Quality attributes of biomass are critical to account for as well. Low energy content combined with low bulk density results in a large volume of biomass to collect, store, and transport. This makes biomass procurement very expensive (Atashbar, Labadie, & Prins, 2016). Additionally, moisture, energy and ash contents, as well as particle size determine the type of preprocessing, storage, and conversion technologies that can be selected. For instance, wood chips containing bark cannot be used for pellet production due to high ash content (Thek & Obernberger, 2012). Wood pellet production requires biomass with a moisture content around 10% and a particle size of around 4 mm (Thek & Obernberger, 2012). Therefore, utilizing drier biomass types that are already available in small particle sizes can reduce preprocessing costs. Covered storage facilities are more appropriate for dried biomass, (e.g.,
shavings), whereas open-air storage facilities are used mostly to store biomass with higher moisture content (e.g., tops and branches) (Gold & Seuring, 2011).

Equipment and machinery that are selected for performing the activities in the upstream supply chain influence the delivered cost of biomass. For instance, truck transportation might be more economical for delivering biomass over short transportation distances; whereas water and railway transportation might be more economical than truck transportation over longer transportation distances as large volumes of biomass can be shipped in one single trip (Asikainen, 2001; Karttunen et al., 2012; Tahvanainen & Anttila, 2011). For the same reason, double trailer trucks can be more economical than single-trailer trucks for transportation over long distances (Sessions et al., 2013). Machine interactions and interdependencies are also important to account for. For instance, trucking and chipping become interdependent in a logistics system where transportation is done immediately after chipping. In such a system, the transportation time depends on the productivity of the chipping process. Additionally, technical and operational disturbances (e.g. machine breakdowns) in the chipping process can delay transportation, and therefore interrupt the supply of biomass feedstock to the conversion facilities (Talbot & Suadicani, 2005). In this system, comminution cannot start before the truck arrives, therefore, any delay in transportation creates costly idle times for the chipper (Talbot & Suadicani, 2005) as well. Due to the interdependencies, ignoring machine interactions can lead to underestimating the costs (Talbot & Suadicani, 2005). It is worth considering that the productivity of each stage is impacted by several uncontrollable factors; terrain (slope) and road conditions (gravel, dirt), stand characteristics (area, size, species), and weather condition (precipitations and temperature) are some examples (Sessions et al., 2013).

**Important considerations in the midstream supply chain**

Several attributes related to biomass conversion influence the economic feasibility of using forest-based biomass for energy and fuel generation. One major factor to consider is achieving economy of scale since bioenergy and biofuel technologies are capital intensive (Sims, 2013). Unlike many other industries, larger capacities do not necessarily guarantee less expensive bioenergy and biofuel production (Sims, 2013). Large scale bioconversion facilities need more biomass to be procured from farther distances. This drives up the procurement (purchase, preprocessing, and transportation) and storage costs and therefore imposes economic challenges in achieving economy of scale (Caputo, Palumbo, Pelagagge, & Scacchia, 2005; Dwivedi & Alavalapati, 2009; Fischer & Pigneri, 2011). The conversion efficiency also influences the economics of biomass supply chains. To generate a given quantity of a product, fewer amounts of biomass need to be procured for technologies with higher efficiency than for those with lower efficiency. Therefore, some savings may incur in biomass
procurement costs. However, cost savings due to higher efficiencies may not offset the high capital and labor costs of energy generation using more efficient technologies (Varela, Sáez, & Audus, 2001).

- **Important considerations in the downstream supply chain**

Product storage and distribution costs should also be considered as an influencing factor in the economic viability of bioenergy and biofuel investments. This is especially important in the case of biofuel and biochemical products, for which special handling and storage equipment is required (Wright, Daugaard, Satrio, & Brown, 2010). For instance, because of high acidity, stainless material should be used for handling pyrolysis bio-oil to avoid corrosion (Wright et al., 2010). Additionally, depending on the location of the conversion facilities and demand points, different transportation modes, e.g., rail, truck, and water transportation might be needed.

- **Uncertainty across the forest-based biomass supply chain**

Uncertainty, which refers to the lack of reliable data and variations in data, exists in all dynamic systems (Kangas & Kangas, 2004). Uncertainty could be due to lack of knowledge, measurement errors, incomplete data, and unavailability of information about future events (Kangas & Kangas, 2004). Similar to other industries, forest-based biomass supply chains are subject to numerous sources of uncertainty related to raw material availability and quality, transportation and logistics, production, demand, and prices, as well as governmental and regulatory policies (Awudu & Zhang, 2012). However, there are some sources of uncertainty that are specific to forest-based biomass supply chains.

The quality of wood varies with tree species, as well as stand and site characteristics, tree age, and stand development (van Leeuwen et al., 2011). External factors, including stand density, moisture and nutrient availability, climate, competition with other plants and species, and natural disturbances, e.g., wildfire and pests affect the quality and the availability of forest biomass (van Leeuwen et al., 2011). The availability of wood resources to be harvested as saw-log, pulp-log, and biomass for energy are constrained by many other factors, such as slope, drainage, site productivity, tree size, distance to roads, and ownership types (Butler, Zhao, Kittredge, & Catanzaro, 2010). Furthermore, there are interdependencies among different forest sectors. Hence, the variations in one sector impact other sectors (Shabani, Akhtari, & Sowlati, 2013). For instance, any change in sawmill production levels impacts not only the lumber industry but also the industries, such as bioenergy, that use the residual chips for their production (Shabani et al., 2013).

The economic viability of bioenergy and biofuel production is affected by all the multitude of above-mentioned factors. Therefore, these factors should be addressed when designing and planning efficient forest-based biomass supply chains, in which the focus is to keep biomass feedstock cost-competitive
(Hess, Wright, & Kenney, 2007) and to ensure the continuous biomass feedstock (Sims & Venturi, 2004). In order to facilitate decision-making in such a complex environment, operations research methods, mainly mathematical programming (optimization) and simulation modeling were used in a number of studies in the literature (Ba, Prins, & Prodhon, 2016). In the following sections, an overview of studies that developed optimization and simulation models for biomass supply chain planning is presented.

2.3 Optimization modeling of forest-based biomass supply chains

The reviewed studies herein are divided into three groups based on the decision levels, (i.e., strategic, tactical, and operational) that they tackled.

2.3.1 Studies that developed mathematical programming models for optimizing the strategic design of supply chain.

Table 2-1 lists the publications that optimized the strategic design of the supply chain and presents a detailed summary covering information regarding the case studies and features of the optimization models developed in each study. As listed in Table 2-1, these studies mainly determined the location, capacity, technology of facilities for biomass storage, preprocessing, conversion, and in the case of biofuels (e.g., biodiesel and gasoline) upgrading facilities. The annual flow of biomass and bioproducts within the supply chain network were simultaneously addressed. Mixed integer linear programming (MILP) was predominantly applied in these studies to develop the models for optimizing the supply chain economic performance (i.e., maximizing profit or minimizing the cost).

Several of these studies investigated the integration of biomass and conventional energy careers for energy and fuel production (Chinese & Meneghetti, 2005; Elia et al., 2011; Tong et al., 2014). Several authors studied the integration of biofuel and/or bioenergy production into existing forest products supply chains (Machani, Nourelfath, & D’Amours, 2014, 2015; Svensson & Berntsson, 2011; Svensson et al., 2011; Tay et al., 2013; Tong et al., 2014). Some studies optimized the supply chain design for stand-alone bioenergy generation (Freppaz et al., 2004; Frombo et al., 2009; Keirstead, Samsatli, Pantaleo, & Shah, 2012; Nagel, 2000; Upadhyay, Shahi, Leitch, & Pulkki, 2012) and biofuel production (C. W. Chen & Fan, 2012; de Jong et al., 2017; Ekşioğlu, Acharya, Leightley, & Arora, 2009; Huang et al., 2010; Jonker et al., 2016; Kim, Realff, & Lee, 2011a; Kim, Realff, Lee, et al., 2011; Marvin, Schmidt, & Daoutidis, 2013; Memişoğlu & Üster, 2015; Natarajan, Leduc, Pelkonen, Tomppo, & Dotzauer, 2014; Parker et al., 2010). A few studies optimized the supply chains that included both bioenergy and biofuel production (Cambero, Sowlati, et al., 2015; Leduc, Starfelt, et al., 2010, 2010; Tittmann et al., 2010).
<table>
<thead>
<tr>
<th>Study &amp; Region</th>
<th>Candidate facility type</th>
<th>Model type &amp; Objective function</th>
<th>Uncertainties</th>
<th>Method used to deal with uncertainty</th>
<th>Binary decisions</th>
<th>Continuous decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nagel (2000) Germany</td>
<td>Single heat and power facility</td>
<td>MILP Deterministic Max profit</td>
<td>Fossil fuel and biomass prices</td>
<td>Sensitivity analysis</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Freppaz et al. (2004) Italy</td>
<td>Multiple heat and power facilities</td>
<td>MINLP Deterministic Max profit</td>
<td>Heat demand, Minimum energy demand that must be met using biomass</td>
<td>Sensitivity analysis</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Ekşioglu et al. (2009) US</td>
<td>Multiple collection and ethanol facilities</td>
<td>MILP Deterministic Min cost</td>
<td>Investment cost, Biomass procurement costs, Conversion yields and costs</td>
<td>Sensitivity analysis</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Frombo et al. (2009) Italy</td>
<td>Multiple heat and power facilities</td>
<td>MINLP Deterministic Max profit</td>
<td>Did not consider</td>
<td>N/A</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Feng et al. (2010) Canada</td>
<td>Multiple lumber, pulp, wood chips, heat and power facilities</td>
<td>MILP Deterministic Max profit</td>
<td>Did not consider</td>
<td>N/A</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
Table 2.1 (Continued): Summary of studies that developed optimization models for the strategic planning of forest-based biomass supply chains (MILP: mixed integer linear programming, MILNP: mixed integer non-linear programming, Min: minimization, Max: maximization)

<table>
<thead>
<tr>
<th>Study &amp; Region</th>
<th>Candidate facility type</th>
<th>Model type &amp; Objective function</th>
<th>Uncertainties</th>
<th>Method used to deal with uncertainty</th>
<th>Binary Decisions</th>
<th>Continuous decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Huang et al. (2010) US</td>
<td>Multiple ethanol facilities</td>
<td>MILP Deterministic Min cost</td>
<td>○ Transportation cost ○ Technology capacity ○ Biomass supply</td>
<td>Sensitivity analysis</td>
<td>✓ ✓ ✓ ✓</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Leduc, Starfelt, et al. (2010) Sweden</td>
<td>Multiple integrated ethanol and heat and power facilities</td>
<td>MILP Deterministic Min cost</td>
<td>○ Biomass price and supply ○ Transportation cost ○ Product yield, demand, prices ○ Carbon taxes</td>
<td>Scenario analysis</td>
<td>✓ ✓ ✓ ✓</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Rauch &amp; Gronalt (2010) Austria</td>
<td>Multiple storage and preprocessing facilities</td>
<td>MILP Deterministic Min cost</td>
<td>○ Transportation cost ○ Biomass supply</td>
<td>Sensitivity analysis</td>
<td>✓ ✓ ✓ ✓</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Parker et al. (2010) US</td>
<td>Multiple diesel, gasoline, fatty acids facilities</td>
<td>MILP Deterministic Max profit</td>
<td>○ Biomass price and supply</td>
<td>Sensitivity analysis</td>
<td>✓ ✓ ✓ ✓</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
</tbody>
</table>
Table 2.1 (Continued): Summary of studies that developed optimization models for the strategic planning of forest-based biomass supply chains (MILP: mixed integer linear programming, MILNP: mixed integer non-linear programming, Min: minimization, Max: maximization)

<table>
<thead>
<tr>
<th>Study &amp; Region</th>
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<th>Method used to deal with uncertainty</th>
<th>Binary decisions</th>
<th>Continuous decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tittmann et al. (2010) US</td>
<td>Multiple diesel, gasoline, fatty acid, and heat and power facilities</td>
<td>MILP Deterministic Max profit</td>
<td>o Renewable energy targets o Heat demand</td>
<td>Scenario analysis</td>
<td>✓ ✓ ✓ ✓ ✗</td>
<td></td>
</tr>
<tr>
<td>Elia et al. 2011) US</td>
<td>Multiple coal, biomass, and natural gas to liquids facilities</td>
<td>MILP Deterministic Min cost</td>
<td>o Biomass supply o Hydrogen price</td>
<td>Scenario analysis</td>
<td>✓ ✓ ✓ ✓ ✓</td>
<td></td>
</tr>
<tr>
<td>Kim, Realff, et al. (2011) US</td>
<td>Multiple diesel and gasoline facilities</td>
<td>MILP Deterministic Max profit</td>
<td>o Product demand</td>
<td>Scenario analysis</td>
<td>✓ ✓ ✓ ✓ ✓</td>
<td></td>
</tr>
<tr>
<td>Kim, Realff &amp; Lee (2011) US</td>
<td>Multiple pyrolysis and gasoline facilities</td>
<td>MILP Stochastic Max profit</td>
<td>o Biomass supply o Conversion ratio yields o Product demand and prices</td>
<td>Stochastic programming</td>
<td>✓ ✓ ✓ ✓ ✓</td>
<td></td>
</tr>
<tr>
<td>Svensson, Strömberg &amp; Patriksson (2011) Sweden</td>
<td>Single heat and power facility</td>
<td>MILP Stochastic Max profit</td>
<td>o Biomass prices o Energy prices o Emission reduction targets</td>
<td>Stochastic programming</td>
<td>✓ ✓ ✓ ✓</td>
<td></td>
</tr>
</tbody>
</table>

Location, Size, Type, Biomass flow, Biomass storage, Product flow
Table 2.1 (Continued): Summary of studies that developed optimization models for the strategic planning of forest-based biomass supply chains (MILP: mixed integer linear programming, MILNP: mixed integer non-linear programming, Min: minimization, Max: maximization)

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Location</td>
<td>Size</td>
<td>Type</td>
</tr>
<tr>
<td>Svensson &amp; Berntsson (2011) Sweden</td>
<td>Single heat and power, carbon capture and lignin separation</td>
<td>MILP Stochastic Max profit</td>
<td>o CO₂ charges, o Energy and biomass prices, o Investment cost</td>
<td>Stochastic programming</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Chen &amp; Fan, (2012) US</td>
<td>Multiple ethanol facilities</td>
<td>MILP Stochastic Min cost</td>
<td>o Biomass supply, o Product demand</td>
<td>Stochastic programming</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Keirstead et al. (2012) UK</td>
<td>Single heat and power facility, preprocessing facility</td>
<td>MILP Deterministic Min cost</td>
<td>o Did not consider</td>
<td>N/A</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Upadhyay et al. (2012) Canada</td>
<td>Multiple Power facilities</td>
<td>MINLP Deterministic Min cost</td>
<td>o Did not consider</td>
<td>N/A</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Marvin et al. (2013) US</td>
<td>Multiple ethanol, fast pyrolysis, and bio-oil upgrading facilities</td>
<td>MILP Deterministic Min cost</td>
<td>o Product price</td>
<td>Sensitivity analysis</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
Table 2.1 (Continued): Summary of studies that developed optimization models for the strategic planning of forest-based biomass supply chains
(MILP: mixed integer linear programming, MILNP: mixed integer non-linear programming, Min: minimization, Max: maximization)

<table>
<thead>
<tr>
<th>Study &amp; Region</th>
<th>Candidate facility type</th>
<th>Model type &amp; Objective function</th>
<th>Uncertainties</th>
<th>Method used to deal with uncertainty</th>
<th>Binary decisions</th>
<th>Continuous decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machani, et al. (2014) Canada</td>
<td>Bioenergy and biofuel technologies in a pulp and paper mill</td>
<td>MILP Deterministic Max profit</td>
<td>o Did not consider</td>
<td>N/A</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
| Natarajan et al. (2014) Finland | Multiple Biodiesel facilities | MILP Deterministic Max profit | o Biomass price and supply  
   o Energy prices  
   o Carbon offset prices  
   o Operating scale | Sensitivity and scenario analyses | ✓ | ✓ | ✓ | ✓ |
| Tong et al. (2014) US | Multiple conversion and upgrading facilities | MILP Stochastic Min unit cost | o Biomass supply  
   o Product demand | Robust optimization | ✓ | ✓ | ✓ | ✓ |
| Cambero, Sowlati, et al. (2015) Canada | Multiple heat and power, pellet bio-oil | MILP Deterministic Max profit | o Biomass price and supply  
   o Product demand and price | Sensitivity analysis | ✓ | ✓ | ✓ | ✓ |
| Machani, et al. (2015) Canada | Ethanol production in a pulp and paper mill | MILP Deterministic Max profit | o Technology development  
   o Governmental policy  
   o Marker development  
   o Consumer behaviour | Scenario-based modeling | ✓ | ✓ | ✓ | ✓ |
Table 2.1 (Continued): Summary of studies that developed optimization models for the strategic planning of forest-based biomass supply chains (MILP: mixed integer linear programming, MILNP: mixed integer non-linear programming, Min: minimization, Max: maximization)

<table>
<thead>
<tr>
<th>Study &amp; Region</th>
<th>Candidate facility type</th>
<th>Model type &amp; Objective function</th>
<th>Uncertainties</th>
<th>Method used to deal with uncertainty</th>
<th>Binary decisions</th>
<th>Continuous decisions</th>
</tr>
</thead>
</table>
| Memişoğlu & Üster (2015) US | Multiple ethanol facilities | MILP Deterministic Min cost | o Biomass supply  
 o Conversion yield rate  
 o Product demand  
 o Transportation cost | Scenario analysis | ✓ ✓ ✓ ✓ ✓ |
| Jonker et al. (2016) Brazil | Multiple ethanol facilities | MILP Deterministic Min cost | o Did not consider | N/A | ✓ ✓ ✓ |
| de Jong et al. (2017) Sweden | Multiple biofuel/biocrude facilities | MILP Deterministic Min cost | o Biomass supply  
 o Product demand  
 o Production capacities  
 o Transportation model | Scenario Analysis | ✓ ✓ ✓ ✓ |
2.3.2 Studies that developed mathematical programming models for optimizing the tactical and operational planning of forest-based supply chain.

A number of studies developed optimization models to support decision making at tactical and operational levels. These publications are listed in Table 2-2 for the tactical level and in Table 2-3 for the operational level.

As can be seen in Table 2-2, the main focus for the tactical level planning was on optimizing the flow of biomass within a predetermined supply chain design. Optimizing the flow of biomass involved making decisions related to when and where to preprocess forest residues, the amounts of different types of biomass to transport from each supply source, and the amounts of biomass to store and consume in each period.

Except for Shabani and Sowlati (2013), Shabani et al. (2014) and Shabani and Sowlati (2016), who maximized the profit of electricity production, the other studies considered the flow of biomass to the gate of facilities (upstream supply chain) and therefore minimized the total delivered cost of biomass feedstock (Akhtari et al., 2014a; Eriksson & Björheden, 1989; Gunnarsson et al., 2004; Kanzian et al., 2009). Linear programming (LP) was mainly used for developing optimization models at the tactical level. However, mixed integer linear programming (MILP) and mixed integer non-linear programming (MINLP) models were also applied, respectively in Kanzian et al. (2009) and Shabani & Sowlati (2013).

Operational level planning of forest-based biomass supply chains was dealt with in studies by Han & Murphy (2012), Zamar, Gopaluni & Sokhansanj (2017) and Malladi et al. (2018). In these studies, mixed integer linear programming (MILP) models were used to find the optimal routes for a fleet of vehicles for delivering residues to their users such that their demand is met and total traveled distance and cost are minimized. Malladi et al. (2018) integrated the decisions related to biomass inventory and preprocessing in their vehicle routing optimization model.
Table 2-2: Summary of studies that developed optimization models for the tactical planning of forest-based biomass supply chains
(LP: linear programming, MILP: mixed integer linear programming, MILNP: mixed integer non-linear programming, Min: minimization, Max: maximization)

<table>
<thead>
<tr>
<th>Study &amp; Region</th>
<th>Supply chain entities</th>
<th>Model type &amp; Objective function</th>
<th>Uncertainties</th>
<th>Method used to deal with uncertainty</th>
<th>Tactical decisions addressed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eriksson &amp; Björheden (1989) Sweden</td>
<td>Multiple forest regions, one central preprocessing center, one heating plant</td>
<td>LP Deterministic Min cost</td>
<td>Did not consider</td>
<td>N/A</td>
<td>○ Quantity of biomass to chip, transport, and store</td>
</tr>
<tr>
<td>Gunnarsson et al. (2004) Sweden</td>
<td>Multiple supply areas, several intermediate terminals, several heating plants</td>
<td>MILP Deterministic Min cost</td>
<td>Did not consider</td>
<td>N/A</td>
<td>○ Optimal location and time for chipping biomass ○ Quantity of biomass to chip, transport, and store</td>
</tr>
<tr>
<td>Kanzian et al. (2009) Austrian</td>
<td>Multiple supply areas, several intermediate terminals, several heating plants</td>
<td>MILP Deterministic Min cost</td>
<td>○ Heat demand ○ Biomass supply ○ Transportation cost</td>
<td>Sensitivity and scenario analyses</td>
<td>○ Quantity of biomass to chip, transport, and store</td>
</tr>
<tr>
<td>Shabani &amp; Sowlati (2013) Canada</td>
<td>Multiple supply sources and a heating plant</td>
<td>MINLP Deterministic Max profit</td>
<td>○ Biomass supply and quality ○ Transportation cost ○ Electricity cost</td>
<td>Sensitivity and scenario analysis</td>
<td>○ Quantity of biomass to transport, and store ○ Amount of power to produce</td>
</tr>
<tr>
<td>Akhtari et al. (2014a) Canada</td>
<td>Several supply sources, one terminal storage and a heating plant</td>
<td>LP Deterministic Min cost</td>
<td>○ Biomass price and supply ○ Heat demand</td>
<td>Sensitivity analysis</td>
<td>○ Optimal location and time for chipping biomass ○ Quantity of biomass to chip, transport, and store</td>
</tr>
<tr>
<td>Shabani et al. (2014) Canada</td>
<td>Several supply sources and a heating plant</td>
<td>LP Stochastic Max profit and Min two risk measures</td>
<td>○ Biomass supply</td>
<td>Stochastic programming</td>
<td>○ Quantity of biomass, transport, and store ○ Amount of power to produce</td>
</tr>
</tbody>
</table>
Table 2.2 (Continued): Summary of studies that developed optimization models for the tactical planning of forest-based biomass supply chains (LP: linear programming, MILP: mixed integer linear programming, MILNP: mixed integer non-linear programming, Min: minimization, Max: maximization)

<table>
<thead>
<tr>
<th>Study &amp; Region</th>
<th>Supply chain entities</th>
<th>Model type &amp; Objective function</th>
<th>Uncertainties</th>
<th>Method used to deal with uncertainty</th>
<th>Tactical decisions addressed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shabani &amp; Sowlati (2016) Canada</td>
<td>Several supply sources and a heating plant</td>
<td>LP Stochastic Max profit</td>
<td>○ Biomass supply and quality</td>
<td>Hybrid stochastic &amp; robust optimization</td>
<td>○ Quantity of biomass to transport, and store ○ Amount of power to produce</td>
</tr>
<tr>
<td>Zamar, Gopaluni, Sokhansanj, et al. (2017) Canada</td>
<td>Several forest regions and several power plants</td>
<td>LP Stochastic Min cost</td>
<td>○ Biomass supply and quality</td>
<td>Scenario-based optimization</td>
<td>○ Quantity of biomass to transport to each power plant from each forest regions</td>
</tr>
</tbody>
</table>
Table 2-3: Summary of studies that developed optimization models for the operational planning of forest-based biomass supply chains (MILP: mixed integer linear programming, Min: minimization, Max: maximization)

<table>
<thead>
<tr>
<th>Study &amp; Regions</th>
<th>Supply chain entities</th>
<th>Model type &amp; Objective function</th>
<th>Uncertainties</th>
<th>Method used to deal with uncertainty</th>
<th>Operational level decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Han &amp; Murphy (2012) US</td>
<td>Multiple suppliers and multiple customers</td>
<td>MILP Deterministic Min trucking costs and working hours</td>
<td>o Biomass supply  o Product demand</td>
<td>Scenario analysis</td>
<td>o Daily truck routes  o Number of trucks</td>
</tr>
<tr>
<td>Zamar, Gopaluni &amp; Sokhansanj (2017) Canada</td>
<td>Multiple supply sources, one customer</td>
<td>MILP Stochastic Min energy return on energy invested</td>
<td>o Biomass supply and quality  o Travel times  o Truck set up times  o Loading and unloading times</td>
<td>Quantile-based scenario analysis</td>
<td>o Daily truck routes  o Quantity of biomass to transport</td>
</tr>
<tr>
<td>Malladi et al. (2018) Canada</td>
<td>Multiple supply sources, one preprocessing yard, and multiple customers</td>
<td>MILP Min cost</td>
<td>Did not consider</td>
<td>N/A</td>
<td>o Quantity of biomass to chip, transport, and store  o Number of trucks  o Daily truck routes</td>
</tr>
</tbody>
</table>
Although many studies have been conducted, some areas are still insufficiently explored. First of all, the majority of studies developed deterministic models; in these studies, sensitivity and/or scenario analyses were used as a post-optimality tool to quantify how variations in model input parameters, e.g., biomass supply, procurement costs, product demand, impacted the optimal solution. Post-optimal analysis tools only give information about the performance of the solution and do not provide a single solution that performs well under uncertainty (Bertsimas, Brown, & Caramanis, 2011). A few authors incorporated uncertainties into their models through stochastic programming (Kim, Realff, & Lee, 2011; Shabani et al., 2014; Svensson & Berntsson, 2011; Svensson et al., 2011; Zamar, Gopaluni, & Sokhansanj, 2017; Zamar, Gopaluni, Sokhansanj, et al., 2017) and robust optimization (Tay et al., 2013; Tong et al., 2014), which are the conventional techniques to incorporate uncertainties in modeling (Bertsimas et al., 2011).

Uncertainty gives rise to investment risks and complicates the decision-making process. In such a situation, the investors’ perception of risk becomes an inherent part of decision-making (Yager, 1999). Risk-averse (pessimistic) and risk-seeking (optimistic) investors diverge in their prediction of future conditions and therefore the investment decisions that they make (Chen, 2011). For instance, if two investment alternatives are evaluated to have the same risk but different projected profits, all the investors would choose the alternative with the highest expected profit (Ruppert, Kappas, & Ibendorf, 2013). However, if the alternative with higher profit is predicted to bear more risk, decision making becomes more complex. Unlike the risk-seeking investor, the risk-averse one, who strives for income and certainty, may prefer the less risky alternative despite its lower expected profit (Ruppert et al., 2013). Therefore, it is important to address the investors’ viewpoint of risk when considering uncertainty in making investment decisions for bioenergy and biofuel production.

In previous studies that dealt with strategic planning of forest-based supply chains, the decision maker’s viewpoint with respect to uncertainty (i.e., being pessimistic, optimistic, or somewhere in between) was overlooked, although it was found to be a determining factor in investment decisions in studies in other areas. For instance, Pažek and Rozman (2009) showed that different decision-making viewpoints towards risk would result in the acquisition of different hectares of arable land for pumpkin crop production under uncertain market opportunities. Also, De Anda-Montanez, Salas, and Galindo-Cortes (2017) evaluated different management schemes for sardine fisheries under uncertainty, incorporating various decision-making viewpoints (adverse, prone, and neutral) with respect to risk.

Additionally, often separate models were developed to address different planning levels. In general, when planning is divided into different levels, using solutions from one level may result in sub-optimal or infeasible solutions at another planning level (Andersson, 2005). In order to avoid these issues, a
linkage among decisions of various levels can be formulated. Two different approaches, hierarchical planning and integrated planning, have been used in the literature for this purpose (Schneeweiss, 1999).

In hierarchical planning, the problem is divided into sub-problems that are solved sequentially in one or more iterations (Schneeweiss, 1999). The top-level model includes long term and aggregated (strategic or tactical) decisions (Schneeweiss, 1999). Decisions from the top-level model impose the framework for more detailed decisions at the operational level (Schneeweiss, 1999). The quality of aggregated decisions are then evaluated based on the feedback received from the detailed decisions (Schneeweiss, 1999). An advantage of the hierarchical planning approach is the reduction in complexity (Stadtler & Fleischmann, 2012). This approach has an advantage in the consideration of uncertainties since through this approach it might be possible to include uncertainty only in lower-hierarchy sub-problems, e.g., short-term demand uncertainty (Bitran & Tirupati, 1993). Another benefit of hierarchical planning is that it fits decision-making process of an organization, and therefore it is responsive to conflicting needs of managers at different levels (Vogel, Almada-Lobo, & Almeder, 2017). However, a hierarchical planning model may not yield an optimal solution for a given problem (Schneeweiss, 1999). The consistency between aggregation and disaggregation, which can be done by product, time, and spatial considerations, affects the success of a hierarchical planning procedure (Bitran & Tirupati, 1993). The solution of the top-level (aggregated) model may not yield a feasible solution to the detailed problem. In an illustrative case study, Paradis, LeBel, D’Amours, and Bouchard, (2013) showed the incoherence of the plans from a hierarchical forest planning process at strategic and tactical levels through several simulation iterations. The authors argued that their hierarchical planning process failed to ensure the long-term sustainability of wood supply (e.g. non-declining yields) and to meet the industrial fiber demand over time. In order to improve the implementation of hierarchical production planning, some aggregation and disaggregation techniques including adding additional constraints might be applied (see (Bitran & Tirupati, 1993) for infeasibilities and techniques to resolve infeasibility); however, these techniques, do not guarantee feasibility. Furthermore, they require detailed data and increase the computational efficiency, which defeat the main advantage of hierarchical planning (Bitran & Tirupati, 1993).

As an alternative, the linkage among decisions of various levels can be formulated in a monolithic model, which addresses decisions of different levels simultaneously in a single integrated model (Schneeweiss, 1999). One benefit of a monolithic model is the coordination of adjacent level decisions within the model. While constructing a monolithic model will ensure the optimal solution for a given problem, the major disadvantages of such an approach are the large amount of detailed input data that are required for a long planning horizon and the high computational capacity required for obtaining a
solution (Vogel et al., 2017). Because of the mentioned disadvantages, the monolithic models were not commonly used (Vogel et al., 2017). In 1973, when Hax and Meal (1973) initiated the hierarchal planning approach for solving an integrated production and scheduling problem, common RAM sizes were around 12 kilobytes. In their paper, Hax and Meal (1973) stated that one reason for employing their hierarchal planning approach was that they could not achieve the solution with the available analytical methods and data processing capacities. Today, the computing power has increased significantly. Therefore, a solution from a monolithic problem might be obtainable in a reasonable time. In a recent study, Vogel et al. (2017) compared the performance of hierarchal and monolithic models for a production planning and scheduling problem and showed that within their parameter settings, it was possible to solve the monolithic model. They claimed their monolithic model had a better performance compared with the hierarchal model since the corresponding results were less prone to the aggregation and disaggregation errors (Vogel et al., 2017).

A few monolithic models were developed for integrated strategic and tactical planning of bioethanol supply chains in order to define the number, size and location of collection and processing facilities at the strategic level and logistics management and inventory planning at the tactical level (Ekşioğlu et al., 2009; Lin et al., 2014; Memişoğlu & Üster, 2015). One strength of the integrated models by Ekşioğlu et al., 2009; Lin et al., 2014; and Memişoğlu & Üster, 2015 is that, unlike the majority of strategic models, seasonality in biomass supply and product demand were taken into account. This was done by dividing the planning horizon into multiple time steps that were short enough to accommodate the variations (e.g., daily time steps in Lin et al., 2014, weekly time steps in Ekşioğlu et al., 2009, and monthly in Memişoğlu & Üster, 2015).

Short time steps increase the size of the model, but because a short planning horizon was considered (one year in (Ekşioğlu et al., 2009; Lin et al., 2014)), it was possible to solve the problem. A short planning horizon may not be a proper assumption for forest-based biomass supply chains for two reasons: 1) the allowable harvest levels may vary year-to-year in response to social, economic, environmental, and biological considerations and impact the availability of forest-based residues over the service life of conversion facilities; and 2) contrary to agricultural biomass, the biomass supply locations change over time in view of the long rotation periods of trees. Only Memişoğlu and Üster (2015), addressed variations in biomass supply and demand over a planning horizon of 10 years; however, their model could not be solved without decomposition.

The existing integrated models (Ekşioğlu et al., 2009; Lin et al., 2014; Memişoğlu & Üster, 2015) considered the use of biomass only for bioethanol production and assumed that facilities could be opened only in the first year of the planning horizon. Similar to the majority of the previous studies,
the integrated models developed by r et al. (2009), Lin et al. (2014), and Memişoğlu & Üster (2015) were deterministic.

Therefore, future studies should consider integrating the three planning levels (i.e., strategic, tactical, and operational), while incorporating variations across the supply chain. Such formulation integrates procurement, production, distribution, and sales activities into a single optimization model, integrates geographically dispersed facilities (i.e., suppliers, plants, and markets), and integrates the decisions with different impacts in terms of their duration. Even without considering uncertainty, this formulation presents a large size supply chain model with a large number of variables and requires handling a large amount of data. The size of this problem will grow further when uncertain parameters and variations at the operational level are considered. Therefore, this large model is very difficult in most cases, perhaps impossible to solve with mathematical programming software packages (Lam, Klemeš, & Kravanja, 2011) within a reasonable time. Therefore, there is a need to develop solution procedures that can solve large size problems efficiently.

2.4 Simulation modeling of forest-based biomass supply chains

An alternative approach to consider uncertainty is simulation modeling. Simulation models are used when an analytical-based solution of a model does not exist or is very hard to find (Borshchev, 2013). Some instances are when there is non-linearity in the model, when there are time and causal dependencies, and when there are too many uncertain parameters (Borshchev, 2013). Simulation models can give very detailed information about how a system operates. Examples are information about the disturbances that occur in the system, such as lack of raw materials, blockages or stoppages on a production line (Mardan & Klahr, 2012).

Considering that biomass supply chains are dynamic systems which include a large number of interconnected stages (harvesting, preprocessing, transport, and storage), discrete event simulation (DES) modeling is an appropriate tool for evaluating their performance (Ba et al., 2016).

In the literature, DES modeling was used to address complexities in forest-based biomass supply chain management. A number of studies (summarized in Table 2-4) used DES modeling for forest-based biomass chain planning considering machine productivities and/or interactions among different stages of the chain (Asikainen, 2010; Karttunen et al., 2012; Sessions et al., 2013; Talbot & Suadicani, 2005). In addition to interdependencies, the seasonality in logging operations, which impacts the availability of biomass, was addressed in the DES models developed by Mahmoudi et al., 2009, Mobini et al., 2011, Windisch et al., 2015, and Zhang et al., 2012. The entire supply chain of pellet production from residues generated at wood processing facilities to the end customers was assessed for regular (Mobini et al., 2011).
2013) and torrified pellets (Mobini et al., 2014). Mobini et al. (2013) and Mobini et al. (2014) considered the failure and repair times of the equipment and interdependencies between the processing stages inside the pellet mills. Furthermore, Mobini et al. (2013) and Mobini et al. (2014) accounted for the uncertainty in biomass supply and moisture content in their models.
Table 2-4: Summary of studies that developed simulation models for evaluating forest-based biomass supply chains

<table>
<thead>
<tr>
<th>Study &amp; Region</th>
<th>Supply chain processes</th>
<th>Performance measures</th>
<th>Study details</th>
</tr>
</thead>
</table>
| Talbot & Suadicani (2005) Denmark | Preprocessing, In-field transportation, Highway transportation | Machine idle times, total cost, diesel fuel consumption | **Objective:** Compared the performance of two alternative chipping systems for in-field chipping of trees  
**Uncertainties and complexities:** Stand characteristics, the productivity of machines, delay times, machine failures |
| Mahmoudi et al. (2009) Canada | Harvesting, Preprocessing, High way transportation, Unloading | Quantity, cost and moisture content of delivered biomass, carbon emissions. | **Objective:** Evaluated the performance of the supply chain  
**Uncertainties and complexities:** Seasonality in harvesting, weather conditions e.g. precipitation, the productivity of machines |
| Asikainen (2010) Finland | Preprocessing, Transporting, Unloading | Total cost | **Objective:** Compared the performance of stump crushing at the roadside with that of a conventional system  
**Uncertainties and complexities:** Machine breakdowns and repair times, transportation delays, biomass availability |
| Mobini et al. (2011) Canada | Harvesting, Preprocessing, High way transportation, Unloading | Quantity, cost and moisture content of delivered biomass, carbon emissions. | **Objective:** Evaluated the performance of the supply chain  
**Uncertainties and complexities:** Seasonality in harvesting, weather conditions e.g. precipitation, the productivity of machines, long term variations in biomass availability, different harvesting systems depending on the stand condition |
| Karttunen et al. (2012) Finland | Loading, Waterway transportation, Unloading | Energy density of delivered material, total cost | **Objective:** Compared the performance of waterway transportation with that of truck transportation, considering different alternatives for loading and unloading  
**Uncertainties and complexities:** The productivity of loading and unloading activities, waterway transportation times, barge load size |
<table>
<thead>
<tr>
<th>Study/ Region</th>
<th>Supply chain processes</th>
<th>Performance measures</th>
<th>Study details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhang et al. (2012)</td>
<td>o Harvesting</td>
<td>Total cost, CO₂ emissions, energy consumption</td>
<td><strong>Objective:</strong> Evaluated the performance of the supply chain to the gate of a potential bioethanol facility; the model was run considering 9 potential locations for a bioethanol facility to find the best location for the facility. <strong>Uncertainties and complexities:</strong> Seasonality in biomass availability and restricted access to roads during spring break, road conditions, uncertainties were ignored.</td>
</tr>
<tr>
<td>US</td>
<td>o Preprocessing</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Transportation</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Unloading</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Storage</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mobini et al. (2013)</td>
<td>o Biomass transportation</td>
<td>Total cost, CO₂ emissions, energy consumption</td>
<td><strong>Objective:</strong> Evaluated the performance of a wood pellet supply chain <strong>Uncertainties and complexities</strong> Biomass availability and quality, machine failures and repair times.</td>
</tr>
<tr>
<td>Canada</td>
<td>o Biomass storage</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Pellet production</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Pellet transportation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sessions et al. (2013)</td>
<td>o Mobile chipping</td>
<td>Operating and idle times, chipping and trucking costs</td>
<td><strong>Objective:</strong> Evaluated the economic effect of truck-machine interactions on operating costs, considered several scenarios for different truck types, capacities, and distances <strong>Uncertainties and complexities:</strong> Loading and unloading times, chipping productivity, in-field transportation and highway transportation times, scheduled machine breakdowns.</td>
</tr>
<tr>
<td>US</td>
<td>o Forwarding</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Transportation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mobini et al. (2014)</td>
<td>o Biomass transportation</td>
<td>Total cost, CO₂ emissions, energy consumption</td>
<td><strong>Objective:</strong> Evaluated the integration of torrefaction into pellet production <strong>Uncertainties and complexities:</strong> Biomass supply and quality Equipment performance and breakdowns.</td>
</tr>
<tr>
<td>Canada</td>
<td>o Biomass storage</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Pellet production</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Torrefaction</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Pellet transportation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Windisch et al. (2015)</td>
<td>o Chipping</td>
<td>Total cost, energy density of delivered wood</td>
<td><strong>Objective:</strong> Evaluated and compared the performance of different alternatives for processing piles of residues into woodchips <strong>Uncertainties and complexities:</strong> Seasonality in harvesting, biomass quality, roadside residue pile sizes, machinery breakdown and delays, machine productivities, distances.</td>
</tr>
<tr>
<td>Finland</td>
<td>o Highway transportation</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Transportation</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Simulation models offer great flexibility in incorporating uncertainties; however, they do not provide the optimal solution when there are a large number of possible solutions and when all the combination of solutions cannot be evaluated to find the optimal solution (Figueira & Almada-Lobo, 2014). Considering the ability of simulation models in giving very detailed information about how the system operates and the ability of optimization models to provide optimal or near-optimal solutions, using a combination of optimization and simulation in a hybrid approach increases the reliability of the results, enhances the possibility to find optimal solutions, and promises improved analyses and a better basis for decision-making (Mardan & Klahr, 2012).

Despite its potential in tackling the complexities of biomass supply chains, no previous studies used hybrid optimization-simulation approaches for forest-based biomass supply chain planning. In agricultural biomass supply chain planning literature, Ebadian et al. (2014) is the only author who applied hybrid optimization-simulation for the planning of an agricultural-based biomass supply chain for ethanol production. Ebadian et al. (2014) used their hybrid approach to integrate the tactical and operational levels planning considering uncertainties and dynamics of the supply chain; therefore, the strategic design of the supply chain (i.e., the location and capacity of the ethanol facility) was given in their model. Hence, their optimization model was different from what is done in this dissertation, too.

In the following section, the applications of hybrid simulation optimization approached in other industries are reviewed.

2.5 Hybrid optimization-simulation approaches

In hybrid optimization-simulation, the optimization tool can be used to find the optimal result and the simulation tool can be used to determine whether the solution from the optimization tool is feasible (Mardan & Klahr, 2012). In order to improve the overall result, the solution from the simulation model might be used as feedback to the optimization model (Kulkarni & Venkateswaran, 2014).

One major application of hybrid optimization-simulation in the supply chain planning literature was to address uncertainties (Figueira & Almada-Lobo, 2014) in different areas of decision-making, including inventory management, production planning, transportation and logistics planning, and designing the supply chain (Arisha & Abo-Hamad, 2010) in various industries. For instance, in semiconductor manufacturing, hybrid optimization-simulation was used for inventory planning to incorporate random production capacities and variations in demand when finding optimal safety stock levels (Schwartz, Wang, & Rivera, 2006) and for production planning to consider uncertainties in demand (Uribe, Cochran, & Shunk, 2003). In chemical industries, variations in demand were addressed by using hybrid optimization-simulation approach for determining optimal safety stock levels in polyethylene
production processes (Jung, Blau, Pekny, Reklaitis, & Eversdyk, 2004). In the manufacturing industry, Rao, Scheller-Wolf and Tayur (2000) determined the optimal configuration of the distribution logistics network of construction equipment under demand uncertainties by using hybrid simulation optimization. In (Ko, Ko, & Kim, 2006), random order pick up time, and random travel time were other types of complexities addressed by hybrid simulation distribution network design of a third party logistics service provider.

As discussed earlier, a further complexity in supply chain planning occurs when decisions at different levels of planning are integrated into one model. Strategic, tactical, and operational decisions have mainly been made by developing distinct models without considering the impact of decisions made at a higher level on those in lower levels. An optimization model which is used for integrated tactical and operational or integrated strategic and tactical problems could be very large even when uncertainties are ignored. Simulation models have been used in addition to mathematical programming models to carry out some of the calculations and to reduce the computational loads when solving an integrated production and distribution problems (Gjerdrum, Shah, & Papageorgiou, 2001; Nikolopoulou & Ierapetritou, 2012) under deterministic conditions. Solving integrated problems become more complicated in the presence of uncertainties, as well as non-linear objective functions and/or constraints, which further increase the size of the problem. In these cases, hybrid optimization-simulation models were solved within a reasonable time in previous studies. For example, variations in production and distribution capacities were considered in integrated production and distribution planning (Lee & Kim, 2002; Lim, Jeong, Kim, & Park, 2006). Random machine breakdowns were incorporated in the integrated production and distribution planning in multi-facility, multi-period, and multi-product manufacturing supply chains (Lee, Kim, & Moon, 2002). Also, uncertainties in production and operations (Gnoni, Iavagnilio, Mossa, Mummolo, & Di Leva, 2003), transportation and logistics (Ding, Benyoucef, & Xie, 2005), supply and demand (Hicks, 1999; Keizer, Haijema, Vorst, & Bloemhof-Ruwaard, 2012) were incorporated in integrated problems with different planning horizons. Furthermore, non-linear process dynamics in a biorefinery (Gerailli, Sharma, & Romagnoli, 2014), the non-linear objective function (Truong & Azadivar, 2003), the non-linear cost and delay time functions in the supply chain planning (Almeder, Preusser, & Hartl, 2009) were considered using hybrid optimization-simulation models.

The hybrid optimization-simulation approach also provided a flexible decision-making framework to address qualitative criteria (e.g., the reliability of suppliers) in making strategic decisions on facility location, warehouse location, production capacity, production policy, as well as distribution and transportation modes in (Truong & Azadivar, 2003). Interdependencies among raw material
availability, and production and distribution capacities have also been incorporated in supply chain planning problems (Almeder et al., 2009).

The forest industry took advantage of hybrid models to handle the same types of complexities discussed above. The consequences of implementing harvesting schedules on wildlife habitat were predicted by simulating the schedules obtained from solving an optimization model (Gustafson, Roberts, & Leefers, 2006). The impact of uncertainty in wildfire occurrence on planning fuel management practices was considered in (Rytwinski & Crowe, 2010) and the impact of uncertainty in truck arrival time on raw material procurement was incorporated in (Marques, Sousa, Rönqvist, & Jafe, 2014) by connecting simulation and optimization models. The complexities in describing biodiversity and carbon sequestration decision criteria when optimizing forest conversion were overcome in (Yousefpour & Hanewinkel, 2009), and the complex interaction among various entities over the entire supply chain while optimizing their operation schedules were considered in (Forget, D’Amours, & Frayret, 2008; Frayret, D’Amours, Rousseau, Harvey, & Gaudreault, 2007). Furthermore, hybrid optimization-simulation has been used in (Morneau-Pereira, Arabi, Gaudreault, Nourelfath, & Ouhammou, 2014) to supply a large global optimization problem with enough input data that would not be available without a simulation model.

In Table 2-5, the applications of combined optimization and simulation modeling in the forestry supply chains are summarized.
Table 2-5: Summary of studies that used hybrid optimization-simulation techniques to handle complexities in the forestry supply chain planning

<table>
<thead>
<tr>
<th>System complexity</th>
<th>Author/ Year</th>
<th>Area</th>
<th>Problem(s)</th>
<th>Methods/Tools</th>
<th>Reasons for using the hybrid approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainties</td>
<td>Rytwinski &amp; Crowe (2010)</td>
<td>Forest fire management</td>
<td>Fuel management problem</td>
<td>Mixed integer programming and stochastic simulation</td>
<td>Uncertainties in the spread of fire and forest fire occurrence probabilities</td>
</tr>
<tr>
<td></td>
<td>Marques et al. (2014)</td>
<td>Pulp supply chain</td>
<td>Raw materials reception Problem</td>
<td>Three-phase mathematical programming and discrete event simulation</td>
<td>Uncertainty in arrival times of trucks</td>
</tr>
<tr>
<td>Large-sized global optimization problem</td>
<td>Morneau-Pereira et al.</td>
<td>Lumber production</td>
<td>Integrated wood harvesting, wood allocation, and lumber production problem</td>
<td>Mixed integer programming, Harvesting simulation in FPInterface and sawmill simulation in Optitek</td>
<td>Extensive input data required to run and solve the global optimization problem</td>
</tr>
<tr>
<td>Explaining relationships that cannot be formulated mathematically</td>
<td>Frayret et al. (2007)</td>
<td>Lumber supply chain</td>
<td>Integrated production-distribution problem</td>
<td>Mathematical programming, constraint programming and agent-based simulation</td>
<td>Achieving optimal operational planning considering the interaction among business entities</td>
</tr>
<tr>
<td></td>
<td>Forget et al. (2008)</td>
<td>Lumber supply chain</td>
<td>Integrated production-distribution problem</td>
<td>Mathematical programming, constraint programming and multi-behavior agent-based simulation</td>
<td>Achieving optimal operational planning considering the interaction among business entities and allowing them to adjust their behavior under various situations</td>
</tr>
</tbody>
</table>
Table 2.5 (Continued): Summary of studies that used hybrid optimization-simulation techniques to handle complexities in the forestry supply chain planning

<table>
<thead>
<tr>
<th>System complexity</th>
<th>Author/ Year</th>
<th>Area</th>
<th>Problem(s)</th>
<th>Methods/Tools</th>
<th>Reasons for using the hybrid approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explaining relationships that cannot be formulated mathematically</td>
<td>Gustafson et al. (2006)</td>
<td>Forest management</td>
<td>Timber production optimization and harvest</td>
<td>Linear programming and HARVEST simulator</td>
<td>Assessment of spatial pattern consequences of timber management strategies</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>scheduling</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Explaining relationships that cannot be formulated mathematically</td>
<td>Yousefpour &amp; Hanewinkel (2009)</td>
<td>Forest management</td>
<td>Forest conversion optimization</td>
<td>Dynamic linear programming and Growth</td>
<td>Reproducing new spatial patterns, generating silvicultural interventions,</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>simulator</td>
<td>including biodiversity and carbon sequestration decision criteria</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
2.6 Summary and conclusions

In this chapter, the forest-based biomass supply chain was defined and the important considerations that influence its performance were described. Additionally, modeling approaches that were used to facilitate decision-making for biomass supply chain planning were presented and relevant publications were reviewed.

In the biomass supply chain management literature, a large group of studies relied on mathematical programming approaches to achieve optimal investment decisions for bioenergy and biofuel production (Shabani et al., 2013; Yue et al., 2014). The majority of the existing studies did not account for medium-term variations in biomass supply and demand over the year. This may result in infeasibility of strategic plans at the tactical and operational levels as the need for biomass storage and other operational level constraints are not accounted for at the strategic level. Therefore, integrating tactical and operational level considerations into models that support the strategic decision making should be investigated.

A large body of literature focused on design decisions related to investments in conversion and storage facilities (number, type, and capacity) under deterministic assumptions, although a great deal of uncertainty exists. The importance of uncertainty promoted the development of stochastic models of forest biomass supply chains including stochastic and robust mathematical programming models in a few studies to deal with uncertainties in supply, demand, prices, conversion yields, carbon tax, and emission reduction targets. Uncertainty in biomass quality (e.g., moisture content and heating value) and its impact on the produced energy and the supply chain costs, particularly transportation cost has been overlooked (Shabani & Sowlati, 2016). Furthermore, stochastic forest biomass supply chain models focused on the economic performance of the supply. Due to numerous sources of uncertainty, (e.g., in biomass availability, quality, cost, and bioproduct markets), the risks of bioenergy and biofuel projects are perceived to be significant. In such a situation, the investors’ perception of risk becomes an inherent part of decision making. Despite its role, the investors’ viewpoint toward risk was ignored in the biomass supply chain planning literature.

The application of stochastic and robust optimization models are limited to the problems with a small number of scenarios. Therefore, there is a need for a technique that can handle various sources of uncertainties in large scale problems. Combining optimization and simulation approaches makes it possible to include several sources of uncertainties into the analysis while integrating different planning levels (Sharma, Ingalls, Jones, & Khanchi, 2013).
Chapter 3. Integrated strategic and tactical optimization of forest-based biomass supply chains to consider medium-term supply and demand variations

3.1 Synopsis

In this chapter, the impact of medium-term variations in biomass supply and demand on the strategic design of a forest-based biomass supply chain is investigated. This is achieved by developing an optimization model that integrates strategic and tactical decisions of forest-based biomass supply chains. The integrated model is formulated as a mixed integer linear programming model that maximizes the net present value (NPV) of investment in bioenergy and biofuel projects. At the strategic level, the model prescribes the type, capacity, and the location of bioconversion facilities and the type of products to produce. At the tactical level, the model determines the decision related to the flow of biomass and products among entities of the supply chain on a monthly basis. These decisions are monthly quantities of each type of biomass to transport from each supply source and to store at each location; monthly quantities of each product type to produce and store at each facility location, and monthly quantities of each product type to distribute/transport to their end users. A long planning horizon (20 years) is considered to account for the long-term variations in the annual supply of forest biomass. The issues caused by ignoring medium-term variations are highlighted by comparing the results of the strategic model with those of the integrated model.

3.2 Problem description and model formulation

The supply chain starts at the supply sources where biomass is purchased, preprocessed (loading into a grinder and chipping into a truck), then transported to conversion facilities. Residues from forest areas, i.e., forest residues (top and branches) and mountain pine beetle (MPB) killed logs are chipped at the roadside using mobile chippers. Woodchips are then transported to the conversion facilities immediately after chipping. Sawmill residues, i.e., clean woodchips and hog fuel (mix of bark and sawdust), do not require further preprocessing and they are transported to and used at the conversion facilities in the same form they are generated at sawmills. At the conversion facilities, biomass is transformed into bioenergy (heat and power) and/or biofuels (pyrolysis bio-oil, wood pellets). Various production routes exist for producing each of the potential products.

Bioenergy, namely heat and power, can be: (1) used to meet the entire or a part of the demand for heat (for drying lumber) and power (for running the facility) in sawmills, and (2) distributed to the nearby communities. It is also possible to use conventional energy sources to meet the energy demand of sawmills and conversion facilities. Biofuels, if produced, are sold and transported to their potential
markets. According to this information, the decision to be made are summarized in Table 3-1. In this table, the differences between the integrated model and the strategic version of the model are illustrated.

Table 3-1: Decisions to be determined by the integrated model and the strategic model and their planning period

<table>
<thead>
<tr>
<th>Decisions to be determined and planning period</th>
<th>Integrated model</th>
<th>Strategic model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Annual</td>
<td>Monthly</td>
</tr>
<tr>
<td>The location, type, size, and establishment period</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Transportation quantities of each type of biomass from each supply source to each conversion facility</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Storage quantities of each type of biomass and biofuel products at facilities</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Internal utilization of bioenergy and distribution of biofuels and bioenergy to markets</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>

Since the main contribution of this chapter is related to the integrated model, the detailed mathematical formulation for it is presented first. Thereafter, the differences between the strategic and integrated models are highlighted without presenting the mathematical formulation of the strategic model to save some space.

3.2.1 Integrated model

The schematic view of the integrated strategic and tactical optimization model is illustrated in Figure 3.1. The decision variables of the strategic model are illustrated in the parentheses. The notations used for sets, input parameters, and decision variables in the integrated model are described in Table 3-2.
Figure 3.1: Schematic view of the integrated strategic and tactical optimization model
(The highlighted variables shown in the parenthesis are the decision variables of the strategic mode)
Table 3-2: List of indices, sets, parameters and decision variables of the model

<table>
<thead>
<tr>
<th>Sets/Indices</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>Set of biomass types; index $b \in B$</td>
</tr>
<tr>
<td>I</td>
<td>Set of biomass supply sources; index $i \in I$</td>
</tr>
<tr>
<td>K</td>
<td>Set of candidate conversion technologies; index $k \in K$</td>
</tr>
<tr>
<td>$K_n \subset K$</td>
<td>Set of candidate non-CHP conversion technologies; index $kk \in K$</td>
</tr>
<tr>
<td>L</td>
<td>Set of candidate location for bioconversion facilities; index $l \in L$</td>
</tr>
<tr>
<td>M</td>
<td>Set of markets; index $m \in M$</td>
</tr>
<tr>
<td>P</td>
<td>Set of products (fuel and energy products); index $p \in P$</td>
</tr>
<tr>
<td>$P_e \subset P$</td>
<td>Set of energy products; index $e \in P_e$</td>
</tr>
<tr>
<td>$P_f \subset P$</td>
<td>Set of fuel products, index $f \in P_f$</td>
</tr>
<tr>
<td>S</td>
<td>Set of annual time periods; index $s \in S$</td>
</tr>
<tr>
<td>T</td>
<td>Set of monthly time periods; index $t \in T$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$BC_b$</td>
<td>Biomass type $b$ purchase cost per Odmt</td>
</tr>
<tr>
<td>$CD_{b,e,k}$</td>
<td>Demand for energy type $e$ for processing one unit of biomass type $b$ in technology $k$</td>
</tr>
<tr>
<td>CL</td>
<td>Biomass loss during chipping</td>
</tr>
<tr>
<td>CS</td>
<td>Maximum size of biomass preprocessing, size of a chipper (Odmt.year(^{-1}))</td>
</tr>
<tr>
<td>$DS_{p,l,m}$</td>
<td>Distribution capacity of product $p$ from location $l$ to market $m$</td>
</tr>
<tr>
<td>$EC_{e,l}$</td>
<td>Production/Purchase cost of one unit of conventional energy product $e$ at location $l$</td>
</tr>
<tr>
<td>$ES_{e,l}$</td>
<td>Capacity of producing product $e$ using existing conventional technologies at location $l$</td>
</tr>
<tr>
<td>$FC_k$</td>
<td>Fixed annual cost of operating technology $k$ (insurance, taxes, and maintenance costs)</td>
</tr>
<tr>
<td>$IC_k$</td>
<td>Investment cost of installing technology $k$</td>
</tr>
<tr>
<td>IR</td>
<td>Interest rate</td>
</tr>
<tr>
<td>$MD_{p,m}$</td>
<td>Maximum annual demand for product $p$ in market $m$ (units of product)</td>
</tr>
<tr>
<td>$PA_b^t$</td>
<td>Percentage of total available annual biomass type $b$ in month $t$</td>
</tr>
<tr>
<td>$PC_b$</td>
<td>Preprocessing cost of biomass type $b$ per Odmt</td>
</tr>
<tr>
<td>$PD_{p,m}^t$</td>
<td>Percentage of total annual demand for product $p$ in market $m$ in month $t$</td>
</tr>
<tr>
<td>$PR_{p,m}$</td>
<td>Selling price of one unit product $p$ to market $m$</td>
</tr>
<tr>
<td>$RA_{b,i}^s$</td>
<td>Amount of biomass type $b$ available at supply source $i$ in year $s$</td>
</tr>
<tr>
<td>$SC_{b,l}$</td>
<td>Storage cost of one Odmt of biomass type $b$ at location $l$ per month</td>
</tr>
<tr>
<td>$SC_{f,l}$</td>
<td>Storage cost of one unit of product $f$ at plant location $l$ per month</td>
</tr>
<tr>
<td>$SD_{e,l}^t$</td>
<td>Demand for energy product $e$ in the sawmill in location $l$ in month $t$</td>
</tr>
<tr>
<td>SL</td>
<td>Biomass loss during storage per month</td>
</tr>
</tbody>
</table>
Table 3.2 (Continued): List of indices, sets, parameters and decision variables of the model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS_l, t</td>
<td>Maximum biomass storage capacity at location l</td>
</tr>
<tr>
<td>SS_f, l</td>
<td>Maximum storage capacity for biofuel product f at location l</td>
</tr>
<tr>
<td>TC_b, i, l</td>
<td>Transportation cost of one Odmt of biomass type b from supply source i to location l</td>
</tr>
<tr>
<td>TC_p, l, m</td>
<td>Transportation cost of one unit of product p from location l to the market m</td>
</tr>
<tr>
<td>TS_k</td>
<td>Size of technology k (measured in terms of biomass input)</td>
</tr>
<tr>
<td>UF_k</td>
<td>Utilization factor of technology k</td>
</tr>
<tr>
<td>VC_b, k</td>
<td>Variable cost of processing one Odmt of biomass type b in technology k</td>
</tr>
<tr>
<td>YL_b, p, k</td>
<td>Yield of product p in technology k when using biomass type b</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decision variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>o_b, i, l, t, s</td>
<td>Amount of biomass type b to transport from supply source i to location l in month t of year s</td>
</tr>
<tr>
<td>q_k, l, s</td>
<td>If technology k is selected at location l in the strategic period s</td>
</tr>
<tr>
<td>r_k, l, s</td>
<td>Amount of residual heat from conversion k at location l in month t of year s</td>
</tr>
<tr>
<td>u_b, k, l, t, s</td>
<td>Amount of biomass type b to use in technology k at location l in month t of year s</td>
</tr>
<tr>
<td>w_e, l, s</td>
<td>Amount of bioenergy product e to use for meeting the energy demand of the sawmill at location l in month t of year s</td>
</tr>
<tr>
<td>v_e, b, k, l, s</td>
<td>Amount of bioenergy product e to use for processing biomass type b in technology k in month t of year s</td>
</tr>
<tr>
<td>x_p, l, m, t, s</td>
<td>Amount of product p to distribute from location l to market m in month t of year s</td>
</tr>
<tr>
<td>y_f, l, s</td>
<td>Amount of biofuel product f to store in location l in month t of year s</td>
</tr>
<tr>
<td>z_b, l, t, s</td>
<td>Amount of biomass type b to store in location l in month t of year s</td>
</tr>
</tbody>
</table>

**Objective function**

The objective function is to maximize the net present value (NPV) of the investment as expressed in Eq. (3.1). It is assumed that the conversion technologies are installed at the beginning of a strategic time period. The total profit in year s is calculated considering the revenues and the total costs in that year as shown in Eq. (3.2).

\[
NPV = \sum_s \frac{Profit^s}{(1 + IR)^s} - \frac{\sum_k \sum_l IC_k(q_{k,l}^s - q_{k,l}^{s-1})}{(1 + IR)^{s-1}}
\] (3.1)

\[
Profit^s = Revenue^s - Cost^s
\] (3.2)

The revenue in each year is calculated through Eq. (3.3). The annual revenue is generated from selling bioenergy and biofuels to the markets (first term in Eq. (3.3)). Additionally, when a sawmill sells its residues to a conversion facility at another location, the corresponding revenue is accounted for as revenue for that sawmill (second term in Eq. (3.3)).
The total annual cost in each year consists of biomass purchasing (Eq. (3.4)), preprocessing (Eq. (3.5)), transportation (Eq. (3.6)), and storage costs (Eq. (3.7)), fixed (Eq. (3.8)) and variable operating costs (Eq. (3.9)), biofuel storage cost (Eq. (3.10)), distribution cost of products (Eq. (3.11)), and net savings due to replacing conventional energy sources with biomass (Eq. (3.12)).

\[ \text{Revenue}^s = \sum_{p} \sum_{l} \sum_{m} \sum_{t} \text{PR}_{p,m} \times x^t_{p,l,m} + \sum_{b} \sum_{i' \neq l} \sum_{l} \sum_{t} \text{BC}_b \times o^t_{b,i,l} \]  
\[ (3.3) \]

\[ \text{Biomass purchase cost}^s = \sum_{b} \sum_{l} \sum_{t} \sum_{b} \text{BC}_b \times o^t_{b,i,l} \]  
\[ (3.4) \]

\[ \text{Biomass preprocessing cost}^s = \sum_{b} \sum_{l} \sum_{t} \sum_{b} \text{PC}_b \times o^t_{b,i,l} \]  
\[ (3.5) \]

\[ \text{Biomass transport cost}^s = \sum_{b} \sum_{l} \sum_{t} \sum_{b} \text{TC}_b \times o^t_{b,i,l} \]  
\[ (3.6) \]

\[ \text{Biomass storage cost}^s = \sum_{b} \sum_{l} \sum_{t} \text{SC}_b \times z^t_{b,l} \]  
\[ (3.7) \]

\[ \text{Fixed operating cost}^s = \sum_{k} \sum_{l} \text{FC}_k \times q^k_{b,l} \]  
\[ (3.8) \]

\[ \text{Variable operating cost}^s = \sum_{b} \sum_{k} \sum_{l} \sum_{t} \text{VC}_b \times u^t_{b,k,l} \]  
\[ (3.9) \]

\[ \text{Biofuel storage cost}^s = \sum_{t} \sum_{l} \sum_{f \in p_f} \text{SC}_f \times y^t_{f,l} \]  
\[ (3.10) \]

\[ \text{Product distribution cost}^s = \sum_{p} \sum_{l} \sum_{m} \sum_{t} \text{TC}_{p,m} \times x^t_{p,l,m} \]  
\[ (3.11) \]

\[ \text{Net savings due to replacing conventional energy sources with biomass}^s = \sum_{l} \sum_{t} \sum_{e \in p_e} \text{EC}_e \times \text{SD}^t_{e,l} - \text{EC}_e \times (\sum_{b} \sum_{k} \text{CD}_{b,e,k} \times u^t_{b,k,l} - \sum_{b} \sum_{k} \text{v}^t_{e,b,k} + \text{SD}^t_{e,l} - \sum_{k} \text{w}^t_{e,l}) \]  

- **Constraints**

The mathematical programming model is subjected to a number of constraints which are described below.
**Biomass supply and mass balance constraints**

In each time period, the total amount of biomass to transport from each supply source to different facility locations should not exceed the available supply of biomass. Constraint (3.13) restricts the flow of biomass to its availability at each supply source.

\[
\frac{1}{1-CL} \times \sum_{i} o_{b,i,l}^{t,s} \leq RA_{b,i}^{t,s} \times PA_{b}\quad \forall b \in B \ i \in I \ s \in S \ t \in T \tag{3.13}
\]

Constraints (3.14) and (3.15) state that in each month of each year, the total biomass stored at the end of previous month plus the total biomass that is transported to the conversion facility should be equal to the total amount of biomass to use by conversion technologies plus the total biomass to store at each facility location at the current month. Constraints (3.14) and (3.15) also relate the two planning periods. Constraint (3.14) ensures that the biomass storage quantity at each facility location in the last month \((t = 12)\) of the previous year is the initial inventory of the first month \((t = 1)\) in the current year. Biomass storage in each month \((t > 1)\) of each year is handled in constraint (3.15).

\[
(1 - SL) \times z_{b,l}^{t=12,s-1} + \sum_{i} o_{b,i,l}^{t,s} = \sum_{k} u_{b,k,l}^{t,s} + z_{b,l}^{t,s} \quad t = 1, \ \forall b \in B \ l \in L \ s \in S \tag{3.14}
\]

\[
(1 - SL) \times z_{b,l}^{t-1,s} + \sum_{i} o_{b,i,l}^{t,s} = \sum_{k} u_{b,k,l}^{t,s} + z_{b,l}^{t,s} \quad t > 1, \ \forall b \in B \ l \in L \ s \in S \tag{3.15}
\]

**Product balance constraints**

The flow of biofuels over the planning horizon is handled in the set of constraints (3.16) and (3.17).

\[
y_{f,l}^{t=12,s-1} + \sum_{b} \sum_{k} Y_{b,f,k} \times u_{b,k,l}^{t,s} = \sum_{m} x_{f,l,m}^{t,s} + y_{f,l}^{t,s} \quad t = 1, f \in P_f, l \in L, s \in S \tag{3.16}
\]

\[
y_{f,l}^{t-1,s} + \sum_{b} \sum_{k} Y_{b,f,k} \times u_{b,k,l}^{t,s} = \sum_{m} x_{f,l,m}^{t,s} + y_{f,l}^{t,s} \quad t = 1, f \in P_f, l \in L, s \in S \tag{3.17}
\]

Unlike biofuels, energy products cannot be stored; if produced, the entire amount should be consumed immediately. In combined heat and power (CHP) production, the hot gases exhausted from the turbine or the engine can be entirely or partially extracted into a heat recovery unit for use to meet the heat demand; therefore, there might be some residual heat. Constraint (3.18) ensures that the amount of heat product extracted from a conversion technology, which equals to the heat generated minus amount of

45
residual heat, is used to meet the heat demand of sawmills and conversion facilities and/or sold to the external market.

\[
\sum_b \sum_k Y_{L,b,e,k} \times u_{b,k,l}^{t,s} - \sum_k r_{k,l}^{t,s} \times q_{k,l}^s = +v_e^{t,s} + w_e^{t,s} + \sum_m x_{e,l,m}^{t,s}
\]

\[
e = Heat, \forall \ l \in L \ \ t \in T \ \ s \in S
\]

In Constraint (3.19), it is assured that there is no residual heat in non-CHP technologies.

\[
r_{k,k,l}^{t,s} = 0 \hspace{1cm} \forall \ k k \in K \ \ l \in L \ \ t \in T \ \ s \in S
\]

If power product is generated, it can be used to meet the power demand of sawmills, conversion facilities and/or sold to the external market. Constraint (3.20) guarantees the equilibrium of power production.

\[
\sum_b \sum_k Y_{L,b,e,k} \times u_{b,k,l}^{t,s} = v_{e,l}^{t,s} + w_{e,l}^{t,s} + \sum_m x_{e,l,m}^{t,s} \hspace{1cm} e = Power, \forall \ l \in L \ \ t \in T \ \ s \in S
\]

Constraint (3.21) indicates that in each time period, all the products that are transported/distributed to the markets should not be more than their demands.

\[
\sum_l x_{p,l,m}^{t,s} \leq MD_{p,m} \times PD_{p,m} \hspace{1cm} \forall \ p \in P \ \ m \in M \ \ t \in T \ \ s \in S
\]

Constraints (3.22) and (3.23) prevent the total amount of bioenergy products to use for meeting the energy demand of conversion facilities in Eq. (3.22) and sawmills in Eq. (3.23) from exceeding the corresponding energy demands. In Eq. (3.22), the demand of the conversion technology for bioenergy is estimated as a function of the amount of biomass that should be converted into products.

\[
v_{e,l}^{t,s} \leq \sum_b \sum_k CD_{e,b,k} \times u_{b,k,l}^{t,s} \hspace{1cm} \forall \ e \in P_e \ \ k \in K \ \ l \in L \ \ s \in S \ \ t \in T
\]

\[
\sum_k w_{e,k,l}^{t,s} \leq SD_{e,l} \hspace{1cm} \forall \ e \in P_e \ \ k \in K \ \ l \in L \ \ s \in S \ \ t \in T
\]

Note that, in this model, it is not necessary to meet all the demand using the generated bioenergy.

**Capacity constraints**

The capacity of storage areas should not be exceeded for biomass feedstock (Eq. (3.24)) and biofuel products (Eq. (3.25)).
The total amount of the biomass to transport from cut-blocks as woodchips within the supply chain in a year cannot exceed the total available chipping capacity (Eq. (3.26))

\[
\frac{1}{(1 - \text{CL})} \times \sum_{b} \sum_{j} \sum_{t} \omega_{b,j,t}^{l,s} \leq \text{CS} \quad \forall j \in L \ s \in S \ t \in T
\]

Constraint (3.27) is related to the capacity of production facilities. This constraint prevents an installed conversion facility from functioning under the minimum and over the maximum utilization rates of its installed capacity in each month.

\[
 UF_k \times TS_k \times q_{k,l}^s \leq \sum_{b} u_{b,k,l}^{l,s} \leq TS_k \times q_{k,l}^s \quad \forall p \in P \ k \in K \ l \in L \ s \in S \ t \in T
\]

In Constraint (3.28), transportation/distribution of products is restricted to the distribution capacity from each location to each market.

\[
x_{p,l,m}^{l,s} \leq DS_{p,l,m} \quad \forall p \in P \ l \in L \ m \in M \ t \in T \ s \in S
\]

It is possible to meet sawmills’ and bioconversion facilities’ (if installed) processing heat and/or electricity demand using conventional energy sources. Constraint (3.29) explains this possibility and ensures that the total amount of energy generated using conventional energy sources does not exceed the corresponding production capacity at each location.

\[
\sum_{b} \sum_{k} CD_{e,b,k} \times u_{b,k,l}^{l,s} - \nu_{e,l}^{l,s} + SD_{e,l}^e - w_{e,l}^{l,s} \leq ES_{e,l} \quad \forall e \in P \ l \in L \ s \in S \ t \in T
\]

**Continuous operation**

Finally, Constraint (3.30) ensures that once a conversion facility is opened, it will continue its operations until the end of the planning horizon.

\[
q_{k,l}^{s} \geq q_{k,l}^{s-1} \quad \forall s \in S \ k \in K \ l \in L
\]
**Sign restriction**

In this model, $q_{k,l}^s$ is a binary variable (Eq. (3.1)) and all decision variables $o_{b,l,t}^{t,s}, r_{k,l}^{t,s}, u_{b,k,t}, v_{p,b,k}^{t,s}, w_{p,b,k}^{t,s}, x_{p,l,m}^{t,s}, y_{f,l}^{t,s}, z_{b,l}^{t,s}$ are non-negative continuous variables (Eq. (3.2)).

\[
q_{k,l}^s \in \{ 0,1 \} \quad \forall s \in S \ k \in K \ l \in L \tag{3.1}
\]

\[
o_{b,l,t}^{t,s}, r_{k,l}^{t,s}, u_{b,k,t}, v_{p,b,k}^{t,s}, w_{p,b,k}^{t,s}, x_{p,l,m}^{t,s}, y_{f,l}^{t,s}, z_{b,l}^{t,s} \geq 0 \tag{3.2}
\]

The set of inventory balance constraints (3.14) and (3.15) for biomass, and (3.15) and (3.16) for biofuel are not linear; therefore, they are linearized into a single constraint expressed respectively in constraints (3.33) and (3.34). The linearization is done by defining the binary parameter $\lambda$ which takes a value of 1 if $t = 1$ and 0 otherwise and the parameter $T = 12$, representing the last month of each year.

\[
(1 - SL) \times x_{b,l}^{t+\lambda(T-1)-(1-\lambda)s-\lambda} + \sum_l o_{b,l,t}^{t,s} = \sum_k \sum_b u_{b,k,t}^{t,s} + z_{b,l}^{t,s} \tag{3.33}
\]

\[
\begin{align*}
\lambda &= 1 \quad \text{if } t = 1 \\
\lambda &= 0 \quad \text{Otherwise}
\end{align*}
\]

\[
\sum_f Y_{b,f,k} \times u_{b,k,l}^{t,s} = \sum_f x_{f,l,m}^{t,s} + y_{f,l}^{t,s} \tag{3.34}
\]

\[
\begin{align*}
\lambda &= 1 \quad \text{if } t = 1 \\
\lambda &= 0 \quad \text{Otherwise}
\end{align*}
\]

Constraint (3.18) is non-linear; this constraint is linearized by replacing the non-linear term $\sum_k r_{k,l}^{t,s} \times q_{k,l}^s$ in Constraint (3.18) with the non-negative auxiliary variable $aux_{k,l}^{t,s} \geq 0$ in Constraint (3.36), and introducing the new constraints (3.37) and (3.38) as follows:

\[
\sum_b \sum_k Y_{b,e,k} \times u_{b,k,l}^{t,s} - \sum_k aux_{k,l}^{t,s} = v_{e,l}^{t,s} + w_{e,l}^{t,s} + \sum_m x_{e,l,m}^{t,s} \tag{3.35}
\]

\[e = \text{Heat and } \forall \ l \in L \ s \in S \ t \in T
\]

\[
aux_{k,l}^{t,s} \leq M \times q_{k,l}^s \quad \forall k \in K \ l \in L \ s \in S \tag{3.36}
\]

\[
aux_{k,l}^{t,s} \leq r_{k,l}^{t,s} \quad \forall k \in K \ l \in L \ t \in T \ s \in S \tag{3.37}
\]
\[
\text{aux}_{k,l}^{t,s} \geq r_{k,l}^{t,s} - M \times (1 - q_{k,l}^{t,s}) \quad \forall k \in K \; l \in L \; t \in T \; s \in S
\] (3.38)

The parameter \( M \) in constraints (3.36) and (3.38) denotes a large positive number.

### 3.2.2 Strategic model

The strategic model differs from the integrated model in several aspects. First of all, the strategic model does not include biomass and biofuel storage. Therefore, the decision variables related to optimal biomass storage quantity \( z_{k,l}^{t,s} \) and optimal biofuel storage quantity \( y_{f,l}^{t,s} \) are not included in the strategic model. Hence, they are removed from both biomass balance constrains (3.14) and (3.15) and biofuel balance constraints (3.16) and (3.17). Additionally, the objective function does not include the terms related to biomass and biofuel storage costs expressed respectively in Eq. (3.7) and Eq. (3.10). The rest of the continuous decision variables are replaced by their strategic equivalent illustrated in Figure 3.1. Since the time steps in the strategic model are annual, the equations in the strategic model do not include summation over the monthly time step. All the parameters indicating monthly time steps are aggregated to their annual values.

### 3.3 Technical and economic input parameters of the model

In this section, the model input data related to the case study are presented.

#### 3.3.1 Biomass supply

- **Biomass availability**

  All the facilities are assumed to operate solely on the regional forest-based biomass from two sources: 1) sawmills and 2) forest cut-blocks. Sawmills can provide clean woodchips and hog fuel (a mixture of bark and shavings) to bioenergy and biofuel facilitates. Two types of residues, which are tops and branches and mountain pine beetle-killed logs that are not merchantable as saw-logs are available at each of 1,592 aggregated cut-blocks. The considered cut-blocks are scheduled to be harvested over a 20-year period of 2013-2032 in the considered region. The annual availability of each type of biomass is summarized in Table 3-3.

  Residues from forest cut-blocks are by-products of logging activities. In order to conserve soil productivity, logging operations occur based on soil moisture conditions (Roach & Berch, 2014). Based on the best management practice guidelines for soil conservation, winter months, in which deep snowpack protects the soil, are recommended for logging (Roach & Berch, 2014). During the periods of low snowpack (spring, wet summer, and fall), harvesting load should be reduced (Roach & Berch, 2014). Therefore, logging operations and availability of the residues in British Columbia tend to be...
seasonal depending on soil and weather conditions. It is assumed that the availability of residues from forest cut-blocks changes linearly with seasonal variations in logging activities. Additionally, the considered sawmills are assumed to keep logs in inventory such that they achieve a fixed production level over the year. Table 3-4 illustrates biomass supply seasonal variations.

Table 3-3: Annual available biomass at supply sources

<table>
<thead>
<tr>
<th>Supply source (i)</th>
<th>Biomass type (b)</th>
<th>Location A</th>
<th>Location B</th>
<th>Location C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest cut-blocks</td>
<td>Tops and branches</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mountain pine beetle-killed logs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sawmills</td>
<td>Woodchips</td>
<td>16,150 a</td>
<td>6,000 b</td>
<td>1,422 c</td>
</tr>
<tr>
<td></td>
<td>Hog fuel</td>
<td>8,550 a</td>
<td>1,600 b</td>
<td>1,073 c</td>
</tr>
</tbody>
</table>

a Marinescu (2012)  b Marinescu (2013)  c Akhtari et al. (2014b)

Table 3-4: Variations in biomass availability over the year

<table>
<thead>
<tr>
<th>Supply source (i)</th>
<th>Percentage of total available annual biomass type b in month t (PA_{b,t})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest cut-blocks^a</td>
<td>Jan  13  13  8  0  2  4  11  10  10  9  10  10</td>
</tr>
<tr>
<td>Sawmills</td>
<td>(1/12)×100% of annual available amounts for sawmill clean woodchips and hog fuel in each month</td>
</tr>
</tbody>
</table>

^a Calculated based on monthly logged volumes. The monthly logged volumes were obtained for the years 2001 to 2015 from the Province of British Columbia’s Harvest Billing System (HBS) derived from the Government of British Columbia (2017a)

- **Biomass characteristics**

Biomass properties, including moisture content, energy density, ash content, and bulk density impact its performance as feedstock for bioenergy and biofuel production. Characteristics of different biomass types are summarized in Table 3-5.
Table 3-5: Physical characteristics of residues generated at each of the forest cut-blocks and sawmills

<table>
<thead>
<tr>
<th>Biomass type (b)</th>
<th>Moisture content (MC&lt;sub&gt;b&lt;/sub&gt;) % wet basis</th>
<th>Bulk density (BD&lt;sub&gt;b&lt;/sub&gt;) (kg.m&lt;sup&gt;-3&lt;/sup&gt;)</th>
<th>Energy density (ED&lt;sub&gt;b&lt;/sub&gt;) (GJ.Odmt&lt;sup&gt;-1&lt;/sup&gt;)</th>
<th>Ash content (AC&lt;sub&gt;b&lt;/sub&gt;) %</th>
<th>Biofuel product yield (YL&lt;sub&gt;b,f,k&lt;/sub&gt;)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tops and branches</td>
<td>29.8&lt;sup&gt;a&lt;/sup&gt;</td>
<td>174.1&lt;sup&gt;a&lt;/sup&gt;</td>
<td>19&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.0&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-</td>
</tr>
<tr>
<td>Mountain pine beetle-killed logs</td>
<td>29.8&lt;sup&gt;a&lt;/sup&gt;</td>
<td>174.1&lt;sup&gt;a&lt;/sup&gt;</td>
<td>19&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.92&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.91&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td>Woodchips</td>
<td>30.52&lt;sup&gt;b&lt;/sup&gt;</td>
<td>206.7&lt;sup&gt;b&lt;/sup&gt;</td>
<td>17.72&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.52&lt;sup&gt;d&lt;/sup&gt;</td>
<td>0.91&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td>Hog fuel</td>
<td>30.52&lt;sup&gt;b&lt;/sup&gt;</td>
<td>142.9&lt;sup&gt;b&lt;/sup&gt;</td>
<td>17.80&lt;sup&gt;b&lt;/sup&gt;</td>
<td>4.75&lt;sup&gt;d&lt;/sup&gt;</td>
<td>-</td>
</tr>
</tbody>
</table>

<sup>a</sup> Derived from Case 3 of (Naimi et al., 2009)  <sup>b</sup> Kehbila (2011)  <sup>c</sup> Peng, Bi, Sokhansanj, Lim, Melin (2010)  
<sup>d</sup> Derived from (Rogers & Brammer, 2012) based on ash content

The parameter YL<sub>b,e,k</sub>, which denotes the yield of bioenergy product type e in technology k when using biomass type b, is estimated through Eq. (3.39). In this equation, ED<sub>b</sub> represents the energy density of biomass type b, the data for which was presented in Table 3-5. The parameter Ef<sub>e,k</sub> in Eq. (3.39) represents the efficiency of technology k in producing bioenergy product type e.

\[
YL_{b,e,k} = \frac{ED_b \times Ef_{e,k}}{3.6 \left( \frac{GJ}{MWh} \right)}
\]  

(3.39)

- **Biomass procurement costs**

Biomass procurement costs include biomass purchase price, preprocessing (loading and grinding), and transportation costs. Table 3-6 includes the data for biomass procurement costs. It is assumed that the conversion facilities at sawmills’ location can obtain the residues free of charge. Whereas, the conversion facilities in other locations should pay $10 and $25 per Odmt, respectively, for sawmill hog fuel and woodchips.
Table 3-6: Procurement costs for each type of biomass

<table>
<thead>
<tr>
<th>Biomass type (b)</th>
<th>Purchase cost ($Odmt⁻¹)</th>
<th>Preprocessing cost ($Odmt⁻¹)</th>
<th>Transportation cost ($Odmt⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest residues</td>
<td>1.46 ᵃ</td>
<td>23.33 ᶜ</td>
<td>Provided by FPInnovations</td>
</tr>
<tr>
<td>Mountain pine beetle-killed logs</td>
<td>25 ᵇ</td>
<td>N/A</td>
<td>from each cut-block i to each facility location l</td>
</tr>
<tr>
<td>Woodchips</td>
<td>10 ᵇ</td>
<td>N/A</td>
<td>Calculated in Eq. (3.40)</td>
</tr>
<tr>
<td>Hog fuel</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

ᵃ Calculated based on the minimum prescribed stumpage rate of 0.25 ($m⁻³) obtained from (Government of British Columbia 2018) and bulk density of 0.171 (Odmt.m⁻³) derived from Case 3 of (Naimi et al., 2009)
ᵇ Cambero, Sowlati, et al. (2015) ᶜ Akhtari et al. (2014b)

Transportation cost of sawmill residues from each sawmill to each candidate location is calculated through Eq. (3.40). In this equation, HR denotes the hourly transportation rate and considered to be $124.28 per hour; VL is the volume capacity of a 53’ high chip van which is 113 m³ (Akhtari, Sowlati, and Day 2014b). TDᵢ,ᵢ, is transportation cycle time for a roundtrip from source i to facility location l, and WA is a waiting time of 1 hour for loading and unloading the residues (Akhtari, Sowlati, and Day 2014b). BDᵦ and MCᵦ express, respectively, the bulk density of sawmill residues and their moisture content, the data for which was presented in Table 3-5.

\[
TC_{b,i,l}($Odmt⁻¹) = \frac{HR(TD_{i,i} + WA)}{BD_b \times VL} \times (1 - MC_b) \tag{3.40}
\]

3.3.2 Bioconversion facility data

- Candidate locations for establishing bioconversion facilities

The center point of Location C and the sawmills in locations A and B are considered as candidate locations for bioconversion facilities.

- Alternative conversion technologies

The alternative pathways to produce each of the considered bioproducts and their technical and financial parameters are illustrated in Table 3-7 for bioenergy technologies and in Table 3-8 for biofuel technologies. The size of all the technologies is expressed based on their output product type, except for the pyrolysis technologies, for which the size is based on the biomass input capacity. Monthly biomass input capacity for each bioenergy technology (TSₖ) is obtained through Eq. (3.41):
\[
TS_k (\text{Odmt}) = \frac{1}{12} \times \left( \frac{\text{Cap}_k (\text{MW}) \times 365 \times 24 \times \text{AF}_k (\%)}{\text{Efficiency} \%} \right) \times EC \left( \frac{\text{GJ}}{\text{odt}} \right) \times C \left( \frac{\text{MWh}}{\text{GJ}} \right)
\]

where \( \text{Cap}_k \) is the output capacity of technology \( k \) in MW. \( \text{AF}_k (\%) \) is the availability factor of technology \( k \). Availability factor of a plant is the percentage of time that the system is available to operate. Both planned maintenances and unplanned outages reduce the plant availability. Availability factors for bioenergy (The United States Environmental Protection Agency., 2007) technologies and pyrolysis plants (Rogers & Brammer, 2012) are 90% and for pellet plants are 85% (Gårdbro 2014). C is used to convert GJ to MWh and equals 0.2777 MWh/GJ\(^{-1}\). Efficiency refers to the net energy efficiency, which is the ratio (\%) of the energy output (heat or electricity) divided by the energy contained in the input biomass fuel.

The investment costs in Table 3-7 and Table 3-8 include the capital cost for preparation yard, storage facilities, preprocessing and conversion technologies. In the case of bioenergy generation through gasification, the investment costs exclude the capital for the internal combustion engine as it is assumed that the existing diesel engines can run on the syngas from biomass gasification (Marinescu, 2012, 2013). Annual fixed operating costs (\( FC_k \)) (i.e., maintenance and insurance costs) are considered to be 4% of the investment cost for bioenergy technologies, 4% of the investment cost for pyrolysis technologies (Rogers & Brammer, 2012) and 2.5% of the investment cost for pelletizing technologies (Gårdbro 2014). Additionally, variable costs do not include energy costs, which are accounted for separately.
### Table 3-7: Candidate bioenergy technologies, their efficiencies, and costs

<table>
<thead>
<tr>
<th>Facility type</th>
<th>Technology (k) and utilization rate ((U_F k))</th>
<th>Efficiency (^d)</th>
<th>Investment cost(^a) ($) ((I_C k))</th>
<th>Variable cost(^c) ($ Odmt(^{−1})) ((V_C k))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Size ((Cap_k))</td>
<td>Electrical</td>
<td>Thermal</td>
<td></td>
</tr>
<tr>
<td><strong>Heat only</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Biomass stoker boiler (32.5%)</td>
<td>0.5 MW</td>
<td>-</td>
<td>73.2%</td>
<td>1,902,702</td>
</tr>
<tr>
<td></td>
<td>2 MW</td>
<td>-</td>
<td>79.5%</td>
<td>4,371,262</td>
</tr>
<tr>
<td></td>
<td>3 MW</td>
<td>-</td>
<td>81.4%</td>
<td>5,575,214</td>
</tr>
<tr>
<td></td>
<td>5 MW</td>
<td>-</td>
<td>83.7%</td>
<td>7,574,794</td>
</tr>
<tr>
<td>Gasifier + internal combustion engine (41.2%)</td>
<td>0.5 MW</td>
<td>19.6%</td>
<td>-</td>
<td>1,435,374</td>
</tr>
<tr>
<td></td>
<td>1 MW</td>
<td>21.1%</td>
<td>-</td>
<td>2,790,140</td>
</tr>
<tr>
<td></td>
<td>2 MW</td>
<td>22.6%</td>
<td>-</td>
<td>6,627,952</td>
</tr>
<tr>
<td></td>
<td>3 MW</td>
<td>23.5%</td>
<td>-</td>
<td>9,416,753</td>
</tr>
<tr>
<td></td>
<td>5 MW</td>
<td>24.6%</td>
<td>-</td>
<td>19,322,807</td>
</tr>
<tr>
<td>Oil heater + organic Rankine cycle (41.2%)</td>
<td>0.5 MW</td>
<td>17.9%</td>
<td>-</td>
<td>4,370,263</td>
</tr>
<tr>
<td></td>
<td>1 MW</td>
<td>19.0%</td>
<td>-</td>
<td>6,708,412</td>
</tr>
<tr>
<td></td>
<td>2 MW</td>
<td>20.6%</td>
<td>-</td>
<td>10,466,399</td>
</tr>
<tr>
<td></td>
<td>3 MW</td>
<td>21.8%</td>
<td>-</td>
<td>16,300,526</td>
</tr>
<tr>
<td></td>
<td>5 MW</td>
<td>22.5%</td>
<td>-</td>
<td>26,685,032</td>
</tr>
<tr>
<td>Boiler + steam turbine (41.2%)</td>
<td>0.5 MW</td>
<td>12.4%</td>
<td>-</td>
<td>2,289,530</td>
</tr>
<tr>
<td></td>
<td>1 MW</td>
<td>13.9%</td>
<td>-</td>
<td>4,072,472</td>
</tr>
<tr>
<td></td>
<td>2 MW</td>
<td>15.6%</td>
<td>-</td>
<td>7,745,249</td>
</tr>
<tr>
<td></td>
<td>3 MW</td>
<td>16.6%</td>
<td>-</td>
<td>10,985,048</td>
</tr>
<tr>
<td></td>
<td>5 MW</td>
<td>18.1%</td>
<td>-</td>
<td>16,798,371</td>
</tr>
<tr>
<td>Gasifier + internal combustion engine (41.2%)</td>
<td>0.5 MW</td>
<td>32.3%</td>
<td>41.0%</td>
<td>2,197,916</td>
</tr>
<tr>
<td></td>
<td>1 MW</td>
<td>33.6%</td>
<td>38.6%</td>
<td>3,417,922</td>
</tr>
<tr>
<td></td>
<td>2 MW</td>
<td>35.0%</td>
<td>36.6%</td>
<td>8,119,242</td>
</tr>
<tr>
<td></td>
<td>3 MW</td>
<td>35.8%</td>
<td>35.7%</td>
<td>11,535,523</td>
</tr>
<tr>
<td></td>
<td>5 MW</td>
<td>36.8%</td>
<td>34.6%</td>
<td>23,670,439</td>
</tr>
<tr>
<td>Oil heater + organic Rankine cycle (41.2%)</td>
<td>0.5 MW</td>
<td>11.1%</td>
<td>48.5%</td>
<td>5,353,572</td>
</tr>
<tr>
<td></td>
<td>1 MW</td>
<td>11.4%</td>
<td>50.43%</td>
<td>8,217,805</td>
</tr>
<tr>
<td></td>
<td>2 MW</td>
<td>12.0%</td>
<td>52.1%</td>
<td>12,821,339</td>
</tr>
<tr>
<td></td>
<td>3 MW</td>
<td>11.5%</td>
<td>54.1%</td>
<td>19,968,144</td>
</tr>
<tr>
<td></td>
<td>5 MW</td>
<td>11.8%</td>
<td>55.5%</td>
<td>32,689,164</td>
</tr>
<tr>
<td>Boiler + steam turbine (41.2%)</td>
<td>0.5 MW</td>
<td>18.4%</td>
<td>61.14%</td>
<td>2,804,674</td>
</tr>
<tr>
<td></td>
<td>1 MW</td>
<td>18.4%</td>
<td>61.13%</td>
<td>4,988,788</td>
</tr>
<tr>
<td></td>
<td>2 MW</td>
<td>18.4%</td>
<td>61.12%</td>
<td>9,487,930</td>
</tr>
<tr>
<td></td>
<td>3 MW</td>
<td>18.4%</td>
<td>61.12%</td>
<td>13,423,609</td>
</tr>
<tr>
<td></td>
<td>5 MW</td>
<td>18.3%</td>
<td>61.11%</td>
<td>20,578,005</td>
</tr>
</tbody>
</table>

\(^a\) Investment and variable costs and efficiencies of technologies were derived from (Bridgwater, 1995; Cambero, Sowlati, et al., 2015; Caputo et al., 2005; Dornburg & Faaij, 2001; Marinescu, 2012, 2013). \(^b\) US Energy Information Administration (2018) \(^c\) UK Department of Energy and Climate Change (2014)

\(^d\) Efficiency refers to the net energy efficiency, that is, the ratio (%) of the energy output (heat or electricity) divided by the energy contained in the input biomass fuel.
Table 3.8: Candidate biofuel conversion technologies, their efficiencies, and costs

<table>
<thead>
<tr>
<th>Facility type</th>
<th>Technology (k) and utilization rate (UF_k)</th>
<th>Size (Cap_k)</th>
<th>Product yield (YL_{b,p,k})</th>
<th>Investment cost (I_{C_k})</th>
<th>Variable cost (V_{C_k})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biofuel</td>
<td>Pellet (47%) b</td>
<td>15,000 tonnes.year^{-1}</td>
<td>Varies with type of biomass, summarized in Table 3-5</td>
<td>4,325,361 ($4.14)</td>
<td>14.59 ($)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30,000 tonnes.year^{-1}</td>
<td></td>
<td>6,249,816 ($2.08)</td>
<td>30.42 ($)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>45,000 tonnes.year^{-1}</td>
<td></td>
<td>7,625,640 ($1.68)</td>
<td>24.63 ($)</td>
</tr>
<tr>
<td>Pyrolysis</td>
<td>(80%) c</td>
<td>200 Odmt.day^{-1}</td>
<td></td>
<td>15,664,265 ($2.08)</td>
<td>24.70 ($)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>400 Odmt.day^{-1}</td>
<td></td>
<td>29,346,913 ($1.52)</td>
<td>19.00 ($)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>600 Odmt.day^{-1}</td>
<td></td>
<td>43,006,868 ($1.02)</td>
<td>17.00 ($)</td>
</tr>
</tbody>
</table>

a Investment and variable costs and efficiencies of technologies were derived from (Cambero, Sowlati, et al., 2015; Marinescu, 2012, 2013)  
b Natural Resources Canada (2018b)  
c Rogers and Brammer (2012)

Conversion facilities would require electricity for their operation. Based on the type of technology, drying of biomass might be needed to reach the desired moisture content by the conversion technology. In this case, additional electricity and heat are required. The electricity consumption rates of 240 kWh.Odmt^{-1} and 200 kWh.Odmt^{-1} were considered for facilities with and without drying requirement, respectively (Rogers and Brammer 2012).

Heat demand for water evaporation is assumed to be 1200 kWh per tonne of water (Thek & Obernberger, 2012) and depends on the biomass type as the moisture content is different for each type of biomass and can be calculated through Eq. (3.42).

\[ \text{HD}_k = \left( \frac{1}{1-\text{MC}_{b}(\%)} - \frac{1}{1-\text{MC}_{d,k}(\%)} \right) \times 1200 \text{kWh.tonne}^{-1} \text{ of water} \]  

(3.42)

where HD_k is the heat demand of technology type k for drying biomass from its moisture content as received MC_{b}(\%) to the required moisture content by that conversion technology MC_{d,k}(\%).

Biomass gasification requires biomass with a moisture content not greater than 15%, pelletizing and pyrolysis require moisture contents around 10% (Kehbila, 2011). However, in the case of biomass pyrolysis and gasification, it is assumed that the low-grade waste heat from the conversion process is used to dry biomass to its desired moisture content. Therefore, only the pellet production requires heat from external sources.
• **Bioproducts markets and demand**

Bioenergy products can be used internally at sawmills to replace the conventional energy sources and to meet their energy demand. The data related to energy demand of sawmills and the cost of energy using conventional sources are summarized in Table 3-9.

In Table 3-9, the electricity demand for each sawmill is estimated as a function of its operational capacity. For this purpose, it is assumed that each 3.05 m$^3$ of input log requires 86.6 kWh of electricity (Milota et al., 2007). The chip recovery factor of 0.121 Odmt.m$^{-3}$ (Government of British Columbia, 2017b), which is specific to the sawmills in Interior BC, is used to estimate the log input of each sawmill based on their wood chips production level.

Table 3-9: Annual energy demand of sawmills and cost of conventional energy sources

<table>
<thead>
<tr>
<th>Sawmill location ($l$)</th>
<th>Annual energy demand ($SD_{e,l}$) (MWh)</th>
<th>Conventional energy source</th>
<th>Current generation/purchase costs ($EC_{e,l}$) ($\text{$.MWh}^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3,790 Electricity $^a$ 19,710 Heat $^b$</td>
<td>Diesel</td>
<td>270 $^b$ 90 $^b$</td>
</tr>
<tr>
<td>B</td>
<td>1,408 Electricity $^a$ - Heat $^b$</td>
<td>Diesel</td>
<td>350 $^c$ -</td>
</tr>
<tr>
<td>C</td>
<td>334 Electricity $^a$ - Heat $^b$</td>
<td>Provincial grid</td>
<td>111.60 $^d$ -</td>
</tr>
</tbody>
</table>

$^a$ Derived from (Government of British Columbia, 2017b; Milota et al., 2007)  $^b$ Marinescu (2013)

Any amount of bioenergy that is surplus to the sawmill demand would be distributed to the local grid for selling to nearby communities. The potential external markets for bioproducts are shown in Table 3-10 together with the annual demand at the corresponding markets, the bioproduct selling price and transportation cost of biofuel products to the market.

As mentioned previously, the considered sawmills are assumed to have a fixed monthly production level; therefore, the demand for heat and electricity in sawmills are assumed to be fixed over the year. The market demand for heat and electricity is considered to fluctuate monthly depending on the weather and day and night duration. The demand for biofuel products in their corresponding markets are considered to be fixed over the year. Table 3-11 shows the monthly variations in market demand for bioproducts over the year.
Table 3-10: Maximum annual market demand for bioenergy and biofuels, selling prices and distribution costs

<table>
<thead>
<tr>
<th>Product ($p$)</th>
<th>Market ($m$)</th>
<th>Maximum annual market demand ($MD_{p,m}$)</th>
<th>Selling price ($PR_{p,m}$)</th>
<th>Transportation cost ($TC_{f,l,m}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bio-oil</td>
<td>A distribution center in Location C</td>
<td>122,114.4 m³</td>
<td>266.39 $\cdot$m⁻³</td>
<td>0.26 $\cdot$m⁻³.km⁻¹</td>
</tr>
<tr>
<td>Pellet</td>
<td>North Vancouver port</td>
<td>135,000 tonnes b</td>
<td>160 $\cdot$tonne⁻¹ c</td>
<td>0.09 $\cdot$m⁻³.km⁻¹ b</td>
</tr>
<tr>
<td>Heat</td>
<td>Small to medium institutional and commercial buildings in Location C</td>
<td>12,322 MWh d</td>
<td>95 $\cdot$MWh⁻¹ b</td>
<td>N/A</td>
</tr>
<tr>
<td>Electricity</td>
<td>Community in Location A</td>
<td>6,704 MWh e</td>
<td>106 $\cdot$MWh⁻¹ f</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Community in Location B</td>
<td>39,420 MWh f</td>
<td>106 $\cdot$MWh⁻¹ f</td>
<td></td>
</tr>
</tbody>
</table>

- a Derived from (Marshall, Wu, Mun, & Lalonde, 2014) assuming a quad axle semi tank-trailer with a capacity of 40 m³
- b Cambero, Sowlati, et al. (2015) assuming truck transportation from the facility location to Location C using truck or tank and rail transportation from Location C to North Vancouver export port
- c Argus Media group (2016) d Akhtari et al. (2014b) e BCHydro (2010)
- f Price that BCHydro will pay for biomass-based electricity delivered in Interior BC under Standing Offer Program (BC Hydro, 2016) g Marinescu (2013)

Table 3-11: Variations in market demand for bioproducts over the year

<table>
<thead>
<tr>
<th>Product</th>
<th>Percentage of total annual demand for bioproduct $p$ in market $m$ in month $t$ ($PD_{p,m}^{t}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hea demand b</td>
<td>Jan 15.5  Feb 12.2  Mar 11.4  Apr 9.2  May 4.6  Jun 3.3  Jul 1.7  Aug 2.2  Sep 4.3  Oct 7.7  Nov 9.8  Dec 18.1</td>
</tr>
<tr>
<td>Electricity demand c</td>
<td>Jan 7.6  Feb 7.4  Mar 6.5  Apr 6.6  May 6.6  Jun 7.1  Jul 8.5  Aug 9.1  Sep 12.2  Oct 10.5  Nov 8.8  Dec 9.11</td>
</tr>
</tbody>
</table>

- a Calculated in Akhtari et al. (2014b) b Derived from BCHydro (2010)

The distribution capacity ($DS_{e,l,m}$) of bioenergy products from one plant location to the other locations is assumed to be zero, the distribution capacity ($DS_{f,l,m}$) for biofuel products to the potential markets and bioenergy products from the plant location to the nearby communities are equal to the corresponding demands.
• **Biomass and biofuel storage costs**

In order to calculate the maximum biomass feedstock storage capacity ($SS_f$), according to Koppejan & Loo (2012), it is assumed that a plant would not store more than 10% of its total biomass annual demand. Biomass storage cost ($SC_{b,t}$) includes an investment cost of 194 $.m^{-2}$ (Akhtari et al., 2014b) and annual maintenance and operating cost of 5% of investment cost (Rentizelas et al., 2009). Area required for the corresponding storage capacity is calculated using the conversion factor of 0.171 Odmt.m^{-3} derived from Case 3 of (Naimi et al., 2009) and an area requirement of 0.2 m² for each cubic meter of woodchips (Rauch & Gronalt, 2010). The total investment cost is annualized over a service life of 20 years using an interest rate (IR) of 10%. The total annualized investment cost and operating and maintenance costs are converted to $/Odmt/month considering a number of inventory turnover of 17 (Marinescu, 2012, 2013). The maximum storage capacity is calculated to be 19,710 Odmt which corresponds to a pyrolysis plant of size 600 Odmt.day^{-1}. Biomass loss during storage (SL) is assumed to be 1.1% per month of which 0.1% is storage losses and 1% is loss due to rotting (Nurmi, 1999).

The storage capacity ($SS_{f,t}$) for biofuel products is set to a maximum of 2 weeks of demand. Based on a standard rule of thumb, the inventory carrying (holding) cost is assumed to equal 25% of the value of the inventory on hand of product per year (equivalent to 3.5 value of the product (its selling price) per month) (REM Associates, 2018).

3.4 Results and analysis

Both strategic and integrated models, which are a mixed integer linear programming model, were built and run using AIMMS 4.32™ software on an Intel(R) 3.60 GHz processor. The strategic model included a total of 410,480 decision variables, of which 2400 were integers, and a total of 151,400 constraints and was solved in 37 seconds. The integrated model subjected to constraints (3.13), (3.18) to (3.42). The integrated model had a total of 4,734,483 decision variables (2400 binary) and 2,006,883 constraints and was solved in 2.5 hours. The results of the integrated model are presented below and compared with those from the strategic version of the model.

3.4.1 Supply chain design and economic performance

Table 3-12 summarizes the optimal supply chain design and its economic measures prescribed by the integrated and strategic models. Compared with the strategic model, the integrated model suggested investing in a fewer number of conversion technologies with different technology types and capacities. The supply chain design obtained from the integrated model would require a smaller initial investment and would have a lower total annual cost and revenue as shown in Table 3-12.
Table 3-12: Optimal selection of conversion technologies in the integrated and strategic model

<table>
<thead>
<tr>
<th>Location</th>
<th>Strategic model</th>
<th>Integrated model</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2 MW biomass boiler + steam turbine (CHP)</td>
<td>2 MW biomass boiler + steam turbine (CHP)</td>
</tr>
<tr>
<td></td>
<td>45,000 tonne.year(^{-1}) pellet mill</td>
<td>45,000 tonne.year(^{-1}) pellet mill</td>
</tr>
<tr>
<td>B</td>
<td>1 MW biomass boiler + steam turbine (CHP)</td>
<td>0.5 MW biomass gasifier + Internal combustion engine (Power only)</td>
</tr>
<tr>
<td></td>
<td>45,000 tonne.year(^{-1}) pellet mill</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>0.5 MW biomass boiler + steam turbine (CHP)</td>
<td>1 MW biomass boiler + steam turbine (CHP)</td>
</tr>
<tr>
<td></td>
<td>600 Odmt.day(^{-1}) pyrolysis plant</td>
<td>600 Odmt.day(^{-1}) pyrolysis plant</td>
</tr>
</tbody>
</table>

- **Investment costs**
  - Strategic model: $75,330,530
  - Integrated model: $66,544,590

- **Average annual costs**
  - Strategic model: $29,381,356
  - Integrated model: 23,661,722.02

- **Average annual savings on conventional energy sources**
  - Strategic model: -$1,533,869
  - Integrated model: -1,446,619.66

- **Average annual revenue**
  - Strategic model: $48,605,521.45
  - Integrated model: $40,539,531.06

- **NPV at 10%**
  - Strategic model: $66,084,902
  - Integrated model: $60,821,666

The lower present value of the integrated model’s supply chain design is mainly because of lower revenues resulting from the reduction in pellet production capacity.

### 3.4.2 Biomass procurement

The total amount of biomass (aggregated over 20 years) to transport and the transportation distances to each facility location are reported in Table 3-13.

Except for Location B, where the optimal bioenergy and biofuel production capacities are significantly lower, the required amount of biomass, the number of supply sources, and the distances that should be traveled to procure biomass are greater in the integrated model than those in the strategic model.
### Table 3-13: Optimal amount of biomass to transport, selected suppliers and distances over the planning horizon

<table>
<thead>
<tr>
<th>Location</th>
<th>Total amount of biomass to transport (Odmt)</th>
<th>Number of biomass sources</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Strategic model</td>
<td>Integrated model</td>
</tr>
<tr>
<td>A</td>
<td>1,283,875</td>
<td>1,286,010</td>
</tr>
<tr>
<td></td>
<td>120 cut-blocks within [4-135] km of the plant and the sawmill in Location A</td>
<td>162 cut-blocks within [4-165] km of the plant and the sawmill in Location A</td>
</tr>
<tr>
<td>B</td>
<td>1,1476,55</td>
<td>31,615</td>
</tr>
<tr>
<td></td>
<td>203 cut-blocks within [5-131] km of the plant and 2 sawmills; one at Location B and the one in Location C</td>
<td>11 cut-blocks within [5-36] km of the plant and the sawmill at Location B</td>
</tr>
<tr>
<td>C</td>
<td>3,972,729</td>
<td>3,983,274</td>
</tr>
<tr>
<td></td>
<td>340 cut-blocks within [10-201] km of the plant and all 3 sawmills</td>
<td>729 cut-blocks within [10-260] km of the plant and all 3 sawmills</td>
</tr>
</tbody>
</table>

#### 3.4.3 Production levels

The proposed average annual production amounts of different types of product are compared based on the results from the integrated and strategic models in Table 3-14.

### Table 3-14: Average annual amount of bioenergy and biofuel prescribed to produce in each location

<table>
<thead>
<tr>
<th>Product</th>
<th>Strategic model</th>
<th>Integrated model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Location A</td>
<td>Location B</td>
</tr>
<tr>
<td>Heat (MWh)</td>
<td>50,902</td>
<td>25,521</td>
</tr>
<tr>
<td>Power (MWh)</td>
<td>15,271</td>
<td>7,659</td>
</tr>
<tr>
<td>Bio-oil (m³)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Pellet (tonne)</td>
<td>45,000</td>
<td>43,615</td>
</tr>
</tbody>
</table>

In Location A, the average annual amount of pellet, and heat and power products to produce are lower in the integrated model than those in the strategic model as shown in Table 3-14. For Location B, the pellet production is eliminated when medium-term variations are incorporated in the integrated model. As a result, the energy demand and therefore energy production drop considerably in this location compared with the strategic case. While the capacity of the pyrolysis plant remains unchanged in the integrated model, the average annual amount of bio-oil to produce is lower in the integrated model as
shown in Table 3-14. Furthermore, power and heat production levels suggested by the integrated model are respectively higher and lower than those suggested by the strategic model in Table 3-14.

In the following, the results of the strategic and the integrated models are further analyzed and differences are discussed for each plant location as follows.

- Location A

As it was mentioned previously, for Location A, the conversion technologies suggested by the integrated model are the same as those suggested by the strategic model (Table 3-12). However, the optimal amounts of biomass to transport are different between the models. Based on the integrated model, a total amount of 1,286,010 Odmt (Table 3-13) is prescribed to transport to Location A over its service life of 20 years. This amount is 2,135 Odmt more than the amount suggested by the strategic model to transport to the same location over the same period of time (Table 3-13). The integrated model selected 162 forest cut-blocks (Table 3-13), approximately 35% more than the number of cut-blocks selected by the strategic model. In the integrated model, the prescribed amount of biomass would be procured from distances between 4 and 165 km (Table 3-13), whereas in the strategic model the transportation distances from the selected cut-blocks to the conversion facilities in Location A are in the range of 4-135 km (Table 3-13). It should be noted that all the 120 cut-blocks suggested by the strategic model are selected in the integrated model as well.

The prescribed amounts of bioenergy and biofuels products to produce are different in the integrated and strategic models as well. According to the plans from the strategic model, the 2 MW CHP plant with an annual capacity of 15,678 MWh would produce an average 15,271 MWh of electricity and 50,902 MWh of heat annually. In the integrated model, the amount of electricity and heat to produce would decrease to 15,160 and 38,519 MWh, respectively. The decrease in pellet production between the models is very small and negligible.

The results of the strategic model, which are at the annual level, were disaggregated at monthly level assuming the monthly variations for biomass supply and product demand illustrated respectively in Table 3-4 and Table 3-11. The breakdown of the results revealed two issues regarding the feasibility of plans from the strategic model. First, although the prescribed amount of biomass to transport to each of the facility locations during January and February would exceed the demand in those months, the extra biomass, as demonstrated in Table 3-15, would not be sufficient to cover the biomass shortage in the March-June period, when access to forest areas are restricted due to weather conditions. Second, analysis of the annual production levels at the monthly level as illustrated in Figure 3.2 (a) for power production, shows that the prescribed capacity is not sufficient to produce prescribed power levels
following the monthly demand patterns. These issues indicate that, for this case study, the results of the strategic model are not feasible at the tactical level.

![Graph](image)

**Figure 3.2:** Prescribed amount of power to produce and available power production capacity of selected conversion technologies in year 1 from (a) strategic model, and (b) integrated model, Location A

The integrated model, which is formulated in a way that the variation could be addressed, resolved the infeasibility issue related to biomass shortage and prevented the infeasibility issue related to production capacity as illustrated in Figure 3.2 (b).

- **Location B**

  In this location, the strategic model suggested a 1 MW CHP plant of biomass boiler and steam turbine and a 45,000 tonne.year⁻¹ pellet plant (Table 3-12). This pellet mill would require an annual amount of 18,597 MWh of heat for drying biomass to the desired moisture content of <10%, which would be provided by the proposed 1 MW CHP plant. The new supply chain design from the integrated model did not include the above-mentioned pellet plant. Since there would not be any demand for the heat product, a CHP plant would not be required. The integrated model suggested a 0.5 MW power only system based on biomass gasification and internal combustion engine technology.

- **Location C**

  In Location C, the strategic model suggested that a 0.5 MW CHP plant would produce enough amount of heat to meet the heat requirements of the nearby community and the power demand of the sawmill facilities and the prescribed 600 Odmt.day⁻¹ biomass pyrolysis (Table 3-12). The prescribed amount of biomass would be transported from 343 biomass supply sources within 10 km to 201 km of this facility location (Table 3-13). The analysis at tactical level revealed that on a monthly basis the capacity of the 0.5 MW CHP facility would not be sufficient to generate the estimated amount of heat to produce (Figure 3.3 (a)). The integrated model, however, selected a larger CHP facility in Location C, which
always would work within the capacity (Figure 3.3 (b)). Compared with the strategic model, the prescribed total amount of biomass to transport to Location C would be 10,545 Odmt more in the integrated model over the service life of the plant (Table 3-13). The required amount of biomass would be obtained from a total of 732 biomass supply sources within 10 to 260 km of the facility location (Table 3-13). It should be noted that locations B and C are relatively close to each other (less than 100 km distance), and the conversion facilities that are located in these two locations would compete for biomass from the same supply sources. In the integrated model, most of the biomass that is within the economic distance of these two facility locations would be transported to Location C and stored there to keep the pyrolysis bio-oil production steady over the year. Consequently, there would not be enough biomass left for pellet production in Location B. Furthermore, compared with the strategic model, the integrated model prescribed a lower production level for heat and bio-oil and a higher production level for electricity in Location C as it can be seen in Table 3-14.

As an instance, the infeasibility issue related to production capacity for heat production in Location C is shown in Figure 3.3 (a). Figure 3.3 (b) illustrates that the infeasibility issue was resolved in the integrated model.

![Figure 3.3: Prescribed amount of heat to produce and available heat production capacity of selected conversion technologies in year 1 from (a) strategic model, and (b) integrated model, Location C](image-url)
Overall, the design prescribed by the strategic model would not be implementable when monthly variations in biomass supply and demand were taken into account. The infeasibility happened because the prescribed amount of biomass to transport to the facilities (from the strategic model) would not be enough to produce the amount of products prescribed by the strategic model (Table 3-15). Moreover, the prescribed amount of products to produce exceeded the production capacity (infeasible situation) (Figure 3.3 (a)). Therefore, developing an integrated strategic and tactical model to accommodate monthly variations in biomass supply and demand seems to be inevitable for the case study considered in this thesis. The integrated model has monthly time steps; therefore, the supply sources and conversion technology types and sizes are selected based on the monthly variations in supply and demand, as well as all the costs that incur at the tactical level.

In the cases with seasonality in biomass supply and demand, even if the variations are not such that infeasibility happens, the integrated model proposed in this chapter can be used for obtaining a better design for the supply chain. The integrated model includes a better estimation of costs and revenues since it accounts for the seasonality and the storage needs. In order to buffer against variations, more biomass would be transported from farther distances, which would increase transportation, preprocessing and storage costs that were not accounted for in the strategic model. When these costs are present, selecting different type or size of conversion technologies might result in an improved objective function.

### 3.5 Summary and conclusions

In this chapter, using a case study in British Columbia, it was illustrated how the design of the supply chain prescribed by a strategic optimization model was not feasible at the tactical level which includes monthly variations in supply and demand. The demand for biomass of the selected conversion facilities
could not be met, and the capacities chosen by the strategic model were not sufficient. The infeasibility issues were addressed by developing a monolithic mixed integer linear programming model that integrated strategic and tactical decisions and incorporated the supply and demand variations over time. Similar to the few existing integrated strategic and tactical models (Ekşioğlu et al., 2009; Memişoğlu & Üster, 2015), decisions related to the location, capacity, and type of technology to be installed were made at the strategic level, while transported quantities of biomass from supply sources to conversion facilities and products from conversion plants to markets, and storage quantities of biomass and final biofuel products were addressed at the tactical level. In contrast to single product supply chains in models (Ekşioğlu et al., 2009; Lin et al., 2014; Memişoğlu & Üster, 2015), the integrated model in this work was developed for a supply chain consisting bioenergy and biofuel production. In the proposed model in this chapter, conventional energy sources e.g. diesel and hydroelectricity were included as an alternative source for energy generation to account for the impact of their prices on the feasibility of opening bioconversion facilities. Instead of considering only the supply chain costs, the product portfolio was optimized taking into account the profit of various products by maximizing the net present value of the network. Additionally, in previous models (Ekşioğlu et al., 2009; Lin et al., 2014; Memişoğlu & Üster, 2015), conversion facilities could be established only at time zero; however, considering that the future conditions (e.g., demand and supply) differ from current ones, this assumption is not a reasonable one. In the model that was developed in this chapter, this assumption was relaxed by adding a temporal dimension to the binary variables, which were used to address the selection of technologies. The results showed that when the medium term variations in supply and demand were taken into account in a monolithic model that integrated strategic and tactical levels, a different network design was suggested. Accordingly, the results showed that integrating strategic and tactical planning levels prevented infeasibility conditions and satisfied the long and medium-term constraints.

Although the positive net present value indicates the financial viability of the proposed investment, the conclusions were based on a deterministic optimization. A part of data was derived from public reports and published literature for similar case studies in other regions. Clearly, there is no guarantee that considered values will be realized. Another part of data (e.g., biomass availability and their transportation costs) was specific to the case study and estimated and supplied by FPInnovations. In their estimation process, specific details related to the stand characteristics, utilization standards, biodiversity and soil conservation considerations, technical and handling losses, and the impact of mountain pine beetle on midterm supply were taken into account. However, since biomass availability is very difficult to be exactly measured (Kim, Realff, & Lee, 2011), the estimations are subject to changes and measurement errors. Overall, the data and hence the net present value of the proposed
investment could vary in reality. Depending on the degree of variability in the net present value that a decision maker is willing to withstand and his/her viewpoint towards risk, the proposed investment might or might not be acceptable. In the next chapter, sensitivity analysis is performed to (1) examine how changes in model parameters impact the proposed investment, and (2) tailor the pessimistic and optimistic future scenarios. Then, the principles of decision making under uncertainty is employed to propose a suitable supply chain design for different decision making perspectives toward the risk.
Chapter 4. Optimizing the design of a forest-based biomass supply chain considering decision maker’s viewpoint towards risk

4.1 Synopsis

In this chapter, first, a series of sensitivity analyses is performed to determine the impact of variations on the proposed supply chain design obtained from the integrated optimization model previously developed in Chapter 3. The variations in the selling price of products, biomass procurement costs, biomass availability, and conventional alternative energy prices are addressed in the sensitivity analysis. The results of the sensitivity analysis are then used to form potential future scenarios, representing optimistic and pessimistic economic conditions. The integrated optimization model in Chapter 3 is solved for each scenario to obtain the corresponding optimal investment decisions. Then, three common rules (criteria) of decision analysis under uncertainty, i.e., maximax, minimax regret, and maximin rules, representing respectively, optimistic, moderately pessimistic, and pessimistic perspectives, are used to analyze investment decisions in bioenergy and biofuel projects. In decision making under uncertainty, which is a rational decision-making approach considering uncertainty and the viewpoint of the decision maker towards risks, it is assumed that the decision maker has the knowledge about future conditions, but the likelihood of their occurrence is unknown. The results of the sensitivity and decision analyses are analyzed and discussed in this chapter.

4.2 Sensitivity analysis

A series of sensitivity analyses regarding biomass procurement costs, selling price of products, conventional energy (diesel, propane, hydro-based electricity) prices, and biomass availability is performed. The following scenarios are tailored for sensitivity analysis, considering ±20% change from the base case scenario.

- ±20% change in biomass procurement cost from the base case scenario. In this scenario, which biomass purchase, preprocessing, transportation, and storage costs are changed at the same time.
- ±20% change in biomass availability
- ±20% change in bioproduct selling prices
- ±20% change in conventional energy prices

The considered range of changes is based on the expected accuracy range of ±20% for feasibility studies in industrial projects suggested by Vancas (2003). This range is selected since the market data for many parameters of the model are not available as the industry is new. Additionally, the variations for the
parameters with available historical data, e.g. wood pellet market price, are checked and turned out to be within the considered range.

4.3 Decision making under uncertainty

The principles of decision analysis for decision making under uncertainty are used to determine which bioenergy and/or biofuel production investment alternative would be preferable based on different views towards risk by decision makers considering uncertainty in biomass availability, biomass procurement and storage costs, selling price of products, and conventional energy prices. In decision making under uncertainty, it is assumed that the decision maker can enumerate the possible future events (states of nature), but the likelihood of their occurrence is unknown (Russel & Taylor III, 2003).

4.3.1 Components of decision making under uncertainty

Based on decision analysis principles, a decision-making situation includes the following main components (Covaliu, 2001; Russel & Taylor III, 2003):

(1) **Decision alternatives**, which are different courses of action that the decision maker can employ (Covaliu, 2001; Russel & Taylor III, 2003). The alternative decisions in this chapter are alternative supply chain designs which differ in technology types, their products, and their capacities. The alternative designs are obtained by solving the integrated optimization model, which was previously developed in Chapter 3, for each state of nature.

(2) **States of nature** are the uncertain future conditions (e.g., economic conditions) that are not within the control of the decision maker (Covaliu, 2001; Russel & Taylor III, 2003). Herein, the optimistic and pessimistic future conditions resulting from changes in biomass availability and procurement cost, bioproduct selling prices, and conventional energy prices are formed based on the results of the sensitivity analysis.

(3) **Payoffs** are the consequences resulting from the combination of each decision alternative and each state of nature (Covaliu, 2001; Russel & Taylor III, 2003). Payoffs in the current chapter are measured in terms of net present value (NPV) through solving the optimization model for the combination of each decision alternative and each state of nature.

(4) **Objective and preferences** with respect to risk (Covaliu, 2001; Russel & Taylor III, 2003). Here, it is assumed that the decision maker’s objective is to maximize the NPV of the investment.

4.3.2 Common decision rules of decision making under uncertainty

Three common decision rules of decision making under uncertainty, i.e., maximax, minimax regret, and maximin rules, representing respectively, optimistic, moderately pessimistic, and pessimistic
perspectives are used to analyze decision making with respect to investing in bioenergy and biofuel projects.

- **Maximax rule**

This rule, which involves choosing the decision alternative that maximizes the maximum payoff, is suitable for a very optimistic or risk-seeking decision maker who assumes that the most favorable condition will prevail. Based on this rule, the alternative that provides the highest payoff calculated using Eq. (4.1) (Carravilla and Oliveira, 2010) is selected. In Eq. (4.1), $v^*$ denotes the highest payoff, $d$ is a decision alternative in the finite set of decision alternatives $D$, $s$ is a state of nature in the finite set $S(d)$, the set of states associated with decision $d$, and $f(d,s)$ denotes the payoff associated with decision $d$ and state $s$.

$$v^* = \max_{d \in D} \{ \max_{s \in S(d)} f(d,s) \} \quad (4.1)$$

- **Maximin rule**

This rule involves selecting the decision alternative that provides the highest payoff if the situation turns out for the worst (Carravilla and Oliveira, 2010). This rule is suitable for a risk-averse decision maker with a pessimistic viewpoint about the future. The pessimist assumes that the worst case will always occur (Carravilla and Oliveira, 2010). The maximin’s highest payoff $v^*$ can be obtained through Eq. (4.2) which is based on Wald’s generic maximin model. Note that the notations for Eq. (4.2) are the same as those for Eq. (4.1).

$$v^* = \max_{d \in D} \{ \min_{s \in S(d)} f(d,s) \} \quad (4.2)$$

- **Minimax regret rule**

This rule takes into account a moderately pessimistic decision maker who tries to avoid regret. This rule involves minimizing the maximum regret using Eq. (4.3). The regret is defined as the opportunity loss by having made the wrong decision, which is the choice other than the one that turns out to be the best (Carravilla and Oliveira, 2010).

$$v^* = \min_{d \in D} \{ \max_{h \in D} \{ \max_{s \in S(d)} (f(h,s) - f(d,s)) \} \} \quad (4.3)$$

In Eq. (4.3), the term “$\max_{h \in D} \{ f(h,s) - f(d,s) \}$” determines the regret experienced with choosing $d$, which is the difference between the highest payoff that a decision maker would have got, had they known the state was $s$ and the payoff obtained by choosing decision $d$. 

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4.4 Results and analyses

4.4.1 Sensitivity analysis

The sensitivity analysis was performed by running and solving the integrated optimization model developed in the previous chapter, using the AIMMS software package. The results are presented and discussed in the following.

Figure 4.1 illustrates the sensitivity of the net present value with respect to the changes in each individual parameter. According to Figure 4.1, bioproduct selling prices have the highest impact on the net present value, followed by biomass procurement cost, biomass availability, and conventional energy prices. Bioproduct selling price is the only factor among the investigated parameters that if it drops by 20% (for all the products simultaneously) can turn the anticipated net present value into a negative value and make the investment economically unacceptable.

- **Sensitivity to bioproduct selling prices**

The net present value (NPV) improves with the increase in bioproduct selling prices (Figure 4.1). This improvement in NPV is directly related to the increased annual revenue, which is the result of selling a greater amount of products (Figure 4.2) at higher prices.
Figure 4.2: Impact of changes in product selling price on suggested production quantities of facilities in the proposed supply chain
(Only the products and locations that are impacted are graphed)

Note that in the base case scenario, pellet and bio-oil production capacities are almost fully utilized; therefore, there is not much room for a significant increase in production levels of these products when bioproduct selling prices increase. In the case of bioenergy production, there is the possibility to increase production levels. Although more revenue could be generated by producing more bioenergy products, the additional biomass procurement and conversion costs would not be offset.

With the decrease in bioproduct selling prices, the NPV decreases because of lower prices coupled with lower sales amount (Figure 4.2), which results in the loss in the revenue. Since the loss in revenue overweighs the savings in total cost, the net present value would decrease dramatically.

As shown in Figure 4.2, pellet production is the most sensitive to the decrease in the bioproduct selling prices. The reason for this rather high impact is that only sawmill clean wood chips and mountain pine beetle-killed residues meet the requirements of pellet production in terms of their ash content. Since sawmill wood chips availability is very limited, mountain pine beetle-killed residues would constitute the major share of the optimal biomass mix for pellet production. However, forest residues in general and specifically mountain pine beetle residues are dispersed over a large area. Within each considered forest cut-block, mountain pine beetle residues account for on average 30% of the total residues. As a result of much-diffused availability, mountain pine beetle residues should be hauled over long distances, which translates into high transportation costs. With low bioproduct selling prices, it would not be economical to procure biomass from distances longer than 55 km of the conversion facility (compared with 165 km in the base case scenario). Therefore, reducing wood pellet production would
decrease the demand for mountain pine beetle residues by 30%, which could be procured within the 55 km of the facility in Location A.

The 15% reduction in the heat and electricity generated in Location A (Figure 4.2) is correlated with the decrease in pellet production in the same location. As pellet production decreases, the heat demand for drying biomass to the desired moisture content of 10% for pellet production and also the electricity demand for running the conversion facility decrease; thus, the bioenergy production in the 2 MW CHP facility in the same location should decrease. As it is illustrated in Figure 4.2, bio-oil production also decreases slightly with a 20% decrease in bioproduct selling price.

- **Sensitivity to biomass procurement cost**

Clearly, the net present value changes inversely with biomass procurement cost (Figure 4.1). Unlike bioproduct selling prices, biomass procurement cost changes the recommended production quantities slightly; the change in NPV is merely related to increases in annual procurement cost. For instance, in the case of a 20% increase in biomass procurement cost, the results recommend a reduction in pellet and bio-oil production by 1.7% (for both products). However, biomass procurement costs influence transportation distances (Table 4-1). As it can be seen in Table 4-1, when biomass procurement cost increases, biomass should be procured from closer distances than those in the base case for the conversion facilities in locations A and C. Whereas the maximum transportation distance remains the same for the conversion facility in Location B, where less amount of biomass is recommended to be procured from the maximum distance.

<table>
<thead>
<tr>
<th>Facility location</th>
<th>Maximum transportation distance (km) based on the biomass procurement cost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20% Decrease</td>
</tr>
<tr>
<td>A</td>
<td>202</td>
</tr>
<tr>
<td>B</td>
<td>29</td>
</tr>
<tr>
<td>C</td>
<td>280</td>
</tr>
</tbody>
</table>

In locations A and B, residues from cut-blocks are partially substituted with the in-house generated sawmill residues, which would be readily available and free of charge. In Location C, the use of harvesting and sawmill residues decreases simultaneously. This is because, with the increase in the sawmill residue utilization in locations A and B, less amount of sawmill residues would be available for transportation to Location C, where availability of sawmill residues is the lowest but the demand for them is highest among the three locations.
• **Sensitivity to biomass availability**

Biomass availability impacts the net present value directly. The foremost cause for this positive relationship is that more biomass would be accessible in closer distances of the facilities when biomass availability increases. As biomass availability increases, a larger portion of biomass demand would be met using the in-house generated sawmill residues; therefore, the demand for harvesting residues and residues from other sawmills decreases. Additionally, as the result of higher biomass availability in closer distances to facilities, transportation distances and therefore biomass procurement cost decrease. Figure 4.3 shows the change in biomass procurement cost with respect to biomass availability.

![Figure 4.3: Impact of changes in biomass availability on biomass procurement cost for each facility location](image)

Overall, with a 20% increase in biomass availability, the procurement cost decreases by up to 24%. Unlike expected, as a result of the increase in biomass availability, there is a decrease in production levels in power facility in Location B (Figure 4.4). This is because, with the increase in biomass availability, the demand for sawmill residues at Location C that should be procured from Location B would decrease. Therefore, the revenue generated from selling sawmill residues would decrease in Location B. In this situation, the results recommend to reduce the amount of power to produce in Location B and rely largely on in-house generated sawmill residues for producing power in the same location. The use of in-house generated sawmill residues would partially eliminate the need for procuring residues from cut-blocks. Since sawmill residues are assumed to be available at no charge, their use would offer some savings in procurement costs which exceed the loss from reduced sales of power product in Location B.
As Figure 4.4 shows, among different products, wood pellet production is sensitive to biomass availability the most, followed by the heat production in Location A. As explained before in the analysis of sensitivity to bioproduct selling prices, pellet production depends largely on mountain pine beetle residues which are much dispersed and their procurement is costly due to high transportation cost. When biomass availability is lower, more amounts of biomass must be procured from farther distances. Therefore, it would be more profitable to produce less quantity of wood pellets as savings in procurement cost would exceed the loss in sales for this product. As pellet production decreases, heat demand for drying biomass decreases; therefore, less amount of heat should be extracted from the CHP system in this location.

- **Sensitivity to conventional energy prices**

When the cost of energy using conventional energy sources increases, the net present value decreases by 4%. While the price of petroleum-based fuels, e.g., diesel, is acknowledged as a key determinant in bioenergy and biofuel production (Winchester & Ledvina, 2017), the results of the current study indicate that it has a small impact on the overall profitability of the proposed investment. This finding may seem counterintuitive at first glance, but it is logical in the context of our case study. The considered communities in this case study are remote communities with limited or no access to energy from the provincial electricity grid or natural gas pipelines. In these communities, diesel is used to generate heat and electricity. Due to the remoteness of communities, the diesel transportation cost is
very high which makes electricity generation so costly that even when it is decreased by 20%, bioenergy generation would still be more cost-effective. The result of this study emphasizes the key role of the conventional energy prices in the viability of energy generation from biomass.

If in a location, energy from conventional sources of energy would be used in addition to bioenergy generated on-site, clearly the expenditure on conventional energy would increase, therefore, the NPV would decrease, and vice versa. For all the considered scenarios, the results suggest that it would be possible to meet the entire energy demand of sawmills and also the proposed conversion facilities with bioenergy in locations A and B, but not in Location C. The reason is that Location C is connected to the provincial grid and can purchase electricity from the grid at a price of $116 per MWh. In the base case scenario, only 9% of the electricity demand of the pyrolysis plant is met using bioenergy generated on-site. The remainder is met using the electricity from the grid. If the cost of the conventional energy increases, the savings from replacing diesel with biomass would increase in locations A and B. However, with the increase in electricity cost from the grid in Location C, the annual expenditure on conventional energy increases in this location. Considering the large size of the pyrolysis facility and its high energy demand, the increase in annual expenditures on conventional energy sources in Location C would exceed the savings due to replacing diesel with biomass in locations A and B; therefore, the overall NPV would decrease.

4.4.2 Decision analysis under uncertainty

The results of sensitivity analysis indicated that the investment in the proposed supply chain is risky as this investment is not resilient to the variations that might happen. Therefore, this investment might or might not be acceptable depending on the decision maker’s viewpoint with respect to risk. In this section, the decisions that might be acceptable by decision makers with different perspectives (optimistic, pessimistic, and moderately pessimistic) are investigated.

Based on the general results of the sensitivity analysis (Figure 4.1), optimistic and pessimistic states of nature, which are the most common scenarios that are considered for evaluating future conditions (Aaker & McLoughlin, 2010), were tailored. Accordingly, the pessimistic state is set for 20% higher biomass procurement cost and conventional energy prices, and 20% lower bioproduct selling prices and biomass availability compared with those in the base case scenario (average state). Conversely, the optimistic state of nature is derived based on 20% lower biomass procurement cost and conventional energy prices, and 20% higher bioproduct selling prices and biomass availability compared with those in the base case scenario. Then, in order to determine the decision alternatives, the integrated optimization model that was previously developed in Chapter 3 was solved for each state of nature explained above. Table 4-2 shows the decision alternatives obtained for each location.
Table 4-2: Alternative supply chain designs

<table>
<thead>
<tr>
<th>Facility location</th>
<th>Decision alternatives</th>
<th>Design I</th>
<th>Design II</th>
<th>Design III</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>(obtained through solving the optimization model assuming the optimistic state of nature)</td>
<td>Combined heat and power facility based on biomass boiler and steam turbine (2 MW)</td>
<td>Combined heat and power facility based on biomass boiler and steam turbine (2 MW)</td>
<td>Combined heat and power facility based on biomass boiler and steam turbine (1 MW)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pellet production facility (45,000 tonne.year⁻¹)</td>
<td>Pellet production facility (45,000 tonne.year⁻¹)</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>(obtained through solving the optimization model assuming the average state of nature)</td>
<td>Combined heat and power facility based on biomass boiler and steam turbine (1 MW)</td>
<td>Power only facility based on biomass gasifier and internal combustion engine (0.5 MW)</td>
<td>Power only facility based on biomass gasifier and internal combustion engine (0.5 MW)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pellet production facility (45,000 tonne.year⁻¹)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>(obtained through solving the optimization model assuming the pessimistic state of nature)</td>
<td>Combined heat and power facility based on biomass boiler and steam turbine (1 MW)</td>
<td>Combined heat and power facility based on biomass boiler and steam turbine (1 MW)</td>
<td>No facility is recommended for installation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pyrolysis bio-oil facility (600 Odmt biomass per day)</td>
<td>Pyrolysis bio-oil facility (600 Odmt biomass per day)</td>
<td></td>
</tr>
</tbody>
</table>

The payoffs corresponding to the outcome of each design for each state of nature were obtained. This was done by fixing the binary variables of the integrated model to one for the technologies in each decision alternative and solving the optimization model for each state of nature. This means that the long term decisions related to the design of the supply chain were considered to be fixed and the optimization model was solved using the new values for costs, prices, and biomass availability parameters.

As illustrated in Table 4-3, based on the maximax rule which represents an optimistic or risk-inclined decision maker, Design I is selected for the supply chain. As tabulated in Table 4-2, this design constitutes 3 small-scale (0.5 MW – 2 MW) bioenergy facilities for heat and power production and 3 biofuel facilities including 2 pellet mills of size 45,000 tonnes per year and one pyrolysis bio-oil facility with the capacity to process 600 Odmt biomass per day. Among the considered decision alternatives Design I is associated with the highest production levels for both bioenergy and biofuel products. Considering the risk aversion nature of investors, it is important to design the supply chain such that an acceptable profit is achieved even in a pessimistic situation. If a project is still attractive under the
pessimistic condition, the decision makers can feel somewhat confident that the project will succeed (Vancas, 2003).

The results of applying the minimax rule (Table 4-43) shows that among the considered alternatives, design III which includes only a 2 MW CHP plant and a 0.5 MW power only facility, is suitable for an extremely risk-averse investor. This is because the pessimistic decision maker would assume a lower selling price for bioproducts and availability of biomass and higher biomass procurement cost than those in the base case. Therefore, procuring biomass, which requires traveling long distances as a result of low biomass availability and high procurement costs, would not be affordable. This design is guaranteed to minimize the losses as it ensures that at least a profit of $10,240,052 could be made even if the worst possible scenario would occur.

Table 4-3: Payoff table showing the net present value of each alternative design for different states of nature

<table>
<thead>
<tr>
<th>Decision alternative</th>
<th>Optimistic</th>
<th>Most likely (base case scenario)</th>
<th>Pessimistic</th>
<th>Maximum payoff</th>
<th>Minimum payoff</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Design I</strong></td>
<td>$172,663,758</td>
<td>$57,647,006</td>
<td>-$50,610,559</td>
<td><strong>172,663,758</strong></td>
<td>-50,610,559</td>
</tr>
<tr>
<td>Design II</td>
<td>$160,206,184</td>
<td>$60,821,666</td>
<td>-$36,645,649</td>
<td>$160,206,184</td>
<td>-36,645,648</td>
</tr>
<tr>
<td><strong>Design III</strong></td>
<td>$10,240,052</td>
<td>$15,122,557</td>
<td>$17,233,883</td>
<td><strong>10,240,052</strong></td>
<td><strong>10,240,052</strong></td>
</tr>
</tbody>
</table>

* Selected in the maximax approach based on the maximum of maximum payoffs (NPV)
**Selected in the maximin approach based on the maximum of minimum payoffs (NPV)

Table 4-4 shows the size of regret for choosing each alternative design if other states of nature would occur.

According to the regret amounts reported in Table 4-4, designs I and III would lead to great losses and therefore may not be preferable by a decision maker who is moderately pessimistic and tries to avoid regret. In this case, and as tabulated in Table 4-4, Design II might be preferable. Similar to Design I, which was recommended based on the optimistic or the maximax rule, Design II, which includes bioenergy and biofuel technologies, is recommended under opportunistic decision making. However, in this design, recommended pellet production capacity is 50% lower than that in Design I.
Table 4-4: The size of regret for choosing each alternative design if other states of nature would occur

<table>
<thead>
<tr>
<th>Decision Alternative</th>
<th>State of nature</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Optimistic</td>
<td>Average</td>
<td>Pessimistic</td>
<td>Maximum regret</td>
<td></td>
</tr>
<tr>
<td>Design I</td>
<td>$0</td>
<td>$3,174,660</td>
<td>$67,844,442</td>
<td>$67,844,442</td>
<td></td>
</tr>
<tr>
<td><strong>Design II</strong>*</td>
<td>$12,457,573</td>
<td>$0</td>
<td>$53,879,532</td>
<td><strong>$53,879,532</strong>*</td>
<td></td>
</tr>
<tr>
<td>Design III</td>
<td>$162,423,705</td>
<td>$45,699,109</td>
<td>$0</td>
<td>$162,423,705</td>
<td></td>
</tr>
</tbody>
</table>

*** Selected in the Mini-Max Regret approach based on the minimum of maximum regret

4.5 Summary and conclusions

The economic performance of the proposed supply chain including bioenergy (heat and power) and biofuel (wood pellet and pyrolysis bio-oil) facilities, which was obtained from the deterministic optimization model in Chapter 3, was evaluated with respect to uncertainty in biomass availability, biomass procurement cost, bioproduct selling prices, as well as conventional energy (e.g. diesel and propane for energy generation) prices through conducting a series of sensitivity analyses. The results of the sensitivity analysis revealed that the net present value of the proposed investment recommended from the deterministic optimization model was sensitive to the changes in parameters and could not remain profitable if the conditions would turn out to be pessimistic. Therefore, depending on the investor’s perspective towards risk, i.e. pessimistic, moderately pessimistic, and optimistic, this design may or may not be acceptable.

In the current chapter, the three common rules of decision analysis for decision making under uncertainty, i.e., maximax, maximin, and minimax regret, were used to represent respectively optimistic, pessimistic, and moderately pessimistic risk viewpoints when determining the supply chain design for investing in bioenergy and biofuel production. The results of the decision analysis recommended investing in biofuel (wood pellet and pyrolysis bio-oil) and bioenergy (heat and/or electricity) production technologies for investors with optimistic and moderately pessimistic viewpoints towards risks because it would yield higher profits than the design for producing only bioenergy. However, further analyses indicated that biofuel production increased the sensitivity of the net present value of the investment considering the high demand for high-quality biomass that would be available in limited quantities and dispersed over large areas and if the conditions turned to the pessimistic scenario, great losses would be expected. Therefore, the designs that include biofuel and bioenergy investments might not be preferable for a pessimistic decision maker. In this case, investing...
in small-scale bioenergy production facilities, in which only in-house generated sawmill residues would be used, could be profitable even if the future conditions turned out to be pessimistic. Therefore, this investment might be appropriate for a pessimist decision maker, who tends to minimize his/her losses. In-house generated sawmill residues are available at no cost for bioenergy production in the considered case study and could provide the opportunity to generate renewable energy that could compete with conventional energy sources.

Recently, the Forest Products Association of Canada (FPAC) undertook a study, named Bio-pathways Project, in order to investigate the opportunities to produce a wide range of bioproducts from wood fiber (FPAC, 2011). The Bio-pathways Project concluded that bioenergy alone would not be sufficient to transform the forest products industry and should be complemented by higher value products, such as bio-oil and pellets, to sustain itself in the long run (FPAC, 2011). In line with this conclusion, the results of the base case scenario in this study showed the prospects of biofuel and bioenergy production as the projected sales of bio-oil and pellet products contributed largely to the profit. However, biofuel production was totally excluded from the optimal supply chain design recommended under the pessimistic approach. Pellet and bio-oil conversion facilities, if installed, would make the investment very sensitive to the changes. This is because these products, especially wood pellets, require large amounts of high-quality biomass, mainly sawmill wood chips and mountain pine beetle residues that are scarce even in the base case scenario, let alone in the pessimistic scenario with low biomass availability assumptions. Bioproduct selling price in the pessimistic scenario would not justify the cost of traveling long distances to procure sufficient quantities of biomass to keep the conversion facilities running at reasonable operating capacities.

In this chapter, only three scenarios, which were optimistic, pessimistic, and average, were considered as states of nature. More scenarios could be developed and analyzed. However, since the variation in several parameters is relevant, the combination can result in a large number of scenarios. Aaker & McLoughlin (2010) defined two or three scenarios as the ideal number with which to work and argued that when considering a larger number of scenarios, the scenario analysis becomes unwieldy and does not have considerable value. Therefore, it is important to define a limited set of scenarios, often the most credible/plausible scenarios; the ones that substantially differ from the present and have the highest impact on the development of a strategy not the ones with the highest probability of occurrence (Aaker & McLoughlin, 2010).

The interest rate is one of the most important factors when evaluating the net present value of an investment; however, the impact of changes in interest rate was not addressed in this chapter. This is because the internal rate of return (IRR) for the proposed investment in Chapter 3 is 21%. This indicates
that the NPV will remain positive while the interest rate is below the IRR. In the previous chapter, a conservative interest rate of 10% was used to calculate the NPV. This interest rate is considerably larger than the one used in similar studies (e.g., 5% in (Cambero, Sowlati, et al., 2015)).

In the next chapter, the feasibility of the strategic supply chain design is evaluated at the operational level by developing and running a discrete event simulation model. In the next chapter, the focus will be specifically on evaluating the impact of inventory management on demand fulfillment, total cost and total CO₂ equivalent emission of the proposed supply chain in Chapter 3.
Chapter 5. Impact of inventory management on demand fulfillment, cost, and emission of forest-based biomass supply chains using simulation modeling

5.1 Synopsis

In this chapter, a simulation model is developed to evaluate and compare the performance of a forest-based biomass supply chain under two inventory management systems based on continuous review systems, namely order-up-to-level, and fixed order quantity inventory management systems. The simulation model is programmed as a discrete event simulation model and consists of three modules: (1) supplier, (2) conversion facility, and (3) order processing and transportation modules. Supplier and conversion facility modules represent, respectively, biomass supply sources and conversion facilities. These two modules are integrated by the flow of information related to orders, as well as the flow of biomass through the third module, order processing and transportation. Three indicators are considered to evaluate the proposed supply chain design: (1) demand fulfillment, (2) total logistics cost, (3) total CO₂ equivalent (CO₂ eq) emission. The simulation terminates after one year; therefore it is categorized as a finite-horizon simulation. First, the considered inventory management systems are described. Then, the structure of the simulation model and its components are explained. Finally, the results are analyzed and discussed.

5.2 Inventory management systems

Biomass storage is required to mitigate the risk associated with biomass availability. Biomass storage can ensure a continuous feedstock supply, avoid interruptions in production and therefore improve the demand fulfillment. Despite reducing the risk of biomass shortage, keeping too much biomass increases the storage and handling costs. At the same time, insufficient inventory of biomass leads to low profit, as some of the revenue might be lost due to interrupted production, or because of the extra money that must be spent to procure biomass, if available, from farther distances. Therefore, biomass inventory management and control, in which the objective is to balance the conflicting goals of improving operational performance and reducing the costs (Axsäter, 2015), can play a key role in the viability of the bioenergy/biofuel projects.

Despite its importance, the inventory management and control is overlooked in the literature related to biomass supply chains. In the current chapter, the objective is to evaluate the impact of inventory management and control system on demand fulfillment, total logistics and inventory costs, and the total CO₂ eq emission of the supply chain. In order to achieve this objective, a discrete event simulation model is developed to evaluate the performance of the proposed supply chain design in Chapter 3, considering two well-known alternative inventory management systems as follows:
1) “Order-up-to-level” system: in this system, when the inventory level falls below a predetermined value known as “the reorder point”, an amount of material (known as “order quantity”) is ordered to bring the inventory level back to a predefined target level (Axsäter, 2015). In this system, order quantity is variable as it depends on the inventory level, which varies with demand.

2) “Fixed order quantity” system: in this system, each time the inventory level reaches the reorder point, regardless of the inventory level, a fixed amount of material (“order quantity”) is ordered (Axsäter, 2015).

In the order-up-to-level system, both the order quantity and the interval between orders can be variable. In the fixed order quantity system, the order quantity is fixed, but the interval between the orders can be variable. Because of these differences, the choice of the inventory control system impacts costs, emissions, and demand fulfillment, and consequently the economic, environmental and operational performance of the supply chains.

5.3 Simulation model

The proposed discrete event simulation (DES) model conceptualizes the supply chain structure illustrated in Figure 5.1. In this figure, commercial harvesting represents the conventional logging system practiced in the Interior Region of British Columbia. In this systems, the trees are felled and forwarded to the roadside with tops and branches intact. Then, they are processed (delimbing and topping) at the roadside (MacDonald, 2007).

Figure 5.2 shows the structure of the proposed simulation model including its components, i.e., simulation modules, input and output data files.

In the following sections, each module is explained in detail.
Figure 5.1: Structure of the biomass supply chain and its operations
Figure 5.2: Structure of the discrete event simulation: the components, the input and output data, and the communication between different components
5.3.1 Supplier module

In this module, sawmills and forest cut-blocks are considered as biomass supply sources. The biomass production is modeled and the availability of each type of biomass at each supply source is tracked as follows:

- **Biomass production at sawmills**

For each sawmill \( l \in L \) (where \( L \) is the set of sawmill locations) and each biomass type generated in sawmills \( b = \{ \text{Clean woodchips, Hog fuel} \} \in B \), an availability rate is calculated based on the annual availability of biomass type \( b \) at sawmill location \( l \) \( (RA_{b,l}^n) \) in year 1 \( (s=1) \) and the number of operating days in month \( t \) \( (ND_t) \) in Eq. (5.1). Then, the parameter \( (BA_{b,l,a}) \), which denotes availability of each type of sawmill residues \( b \) at sawmill location \( l \) at state \( \alpha \), is updated daily using Eq. (5.1). Note that a state is a value of system time at which the value of at least one attribute of one object can be assigned. Here, operating days of months are the state in which biomass availability at sawmills are updated.

\[
BA_{b,l,a} = BA_{b,l,a-1} + \frac{BA_{b,l}}{12 \times ND_t} \quad | \alpha = \text{days and } t = \text{current month} \quad (5.1)
\]

- **Biomass production at forest cut-blocks**

The quantity of logging residues is estimated considering the machine interactions and machine productivity curves; therefore, all the logging operations corresponding to a conventional harvest system are modeled in this module. These operations include felling the trees using feller-bunchers, skidding the trees to the roadside using grapple skidders, and processing at the roadside using dangle head processors.

Logging starts at the forest cut-blocks that are scheduled to be harvested simultaneously. It is not known which of the 379 forest cut-blocks that are scheduled for logging over the first 5-year period would be logged during the first year of operation. Therefore, a random number of forest cut-blocks are selected for logging at the model startup. Random forest cut-blocks are selected one by one until the total available machinery are assigned to selected cut-blocks. Depending on the area, some cut-blocks may need more than one feller-buncher, skidder, or processor. Selection of forest areas results in uncertainty in biomass feedstock availability since some attributes that impact the availability of biomass, such as stem volume, area, age, vary from one cut-block to another cut-block. Also, depending on the area and total volume to extract, logging would end at different points in time. When logging starts at a cut-block \( j \in J \) (where \( J \) is the set of cut-blocks), it is divided into 1-hectare units that go through felling,
skidding, and processing operations one by one. Herein, the period when the logging of one hectare ends defines the state \( \alpha \). After logging each hectare and at state \( \alpha \), the total volume of logs produced at that forest cut-block \( (TV_{j,\alpha}) \) is updated through Eq. (5.2) based on the tree volume per hectare \( (VH_j) \). Then, the availability of each type of logging residues at each forest cut-block at state \( \alpha \), \( (BA_{b,j,\alpha}) \) is updated based on residue recovery ratios \( (RR_{b,j}) \) for tops and branches and mountain pine beetle killed logs using Eq. (5.3).

\[
TV_{j,\alpha} = TV_{j,\alpha-1} + VH_j \quad (5.2)
\]
\[
BA_{b,j,\alpha} = BA_{b,j,\alpha-1} + VH_j \times RR_{b,j} \quad (5.3)
\]

Once logging ends in one cut-block, the closest cut-block, based on the Euclidean distance, will be chosen for logging if the total volume of log collected from all the logged cut-blocks \( (\sum \sum TV_{j,\alpha}) \) has not yet reached the annual harvest level. The seasonality in logging operations, which is due to weather conditions and environmental considerations is modeled in this module based on a monthly logging schedule obtained from the Harvest Billing System. In each month, the total logged volume in all cut-blocks cannot exceed the allowable volume for that month. Otherwise, all the operations are held until next month. Furthermore, in this module, the flow of cut-blocks processed through the model is controlled such that at any point in time, the total log volume collected from all the cut-blocks cannot exceed the annual harvest level.

5.3.2 Conversion facility module

Conversion facility module includes all the facilities \( (k \in K) \) suggested by the integrated optimization model illustrated in Table 3-12 in Chapter 3. It is assumed that the selected facilities keep inventory for different biomass items \( (b \in B) \) and consume biomass for producing energy and fuel products. The major procedures that are modeled in this module are inventory control, supplier selection, placing orders for biomass items, and receiving the biomass items that are transported to each conversion facility.

5.3.3 Inventory control

The inventory control procedure works based on the continuous review system, in which the inventory variables are updated whenever there is a change in the system, i.e., some amount of biomass in the storage is used by the conversion facility, some amount of biomass is ordered, or when some amount of biomass is delivered to the conversion facility, each of these changes constitutes a state of the system. The inventory level \( (IL_{b,k,\alpha}) \) of biomass type \( (b) \) is updated at each facility \( (k) \) at state \( \alpha \) through Eq. (5.4). In this equation, \( OH_{b,k,\alpha} \) is on-hand inventory (what is physically available in the storage at the
conversion facility), $O_{b,k,\alpha}$ is the quantity that has been requisitioned as order, but not received yet (on order or in-transit inventory), and $D_{b,k,\alpha}$ is the amount that is used to meet the daily demand.

$$IL_{b,k,\alpha} = OH_{b,k,\alpha} + OO_{b,k,\alpha} - DM_{b,k,\alpha} \tag{5.4}$$

For each type of biomass, if the on-hand inventory is not sufficient to meet the daily demand, there would be shortage represented through the variable $SH_{b,k,\alpha}$. This variable will be used later to calculate the demand fulfillment of each conversion facility.

If the inventory level for biomass type $b$ in conversion facility $k$ at state $\alpha$ ($IL_{b,k,\alpha}$) falls below its reorder point (ROP$_{b,k}$), an order should be placed to replenish the stock of biomass. The first stage in placing an order is determining the replenishment quantity for the respective biomass type ($RQ_{b,k,\alpha}$) which depends on the type of inventory management system and its control parameters, i.e., order quantity (OQ$_{b,k}$) and reorder point (ROP$_{b,k}$).

In the fixed order quantity system, whenever the reorder point is reached, a fixed quantity of biomass equal to the order quantity parameter (OQ$_{b,k}$) should be ordered. Whereas under the order-up-to-level system, the replenishment quantity should restore the inventory level to a target level. In this system, the order quantity parameter (OQ$_{b,k}$) is used at the target level. Eq. (5.5) is used to calculate the replenishment quantity ($RQ_{b,k,\alpha}$) for the respective biomass type $b$ in conversion facility $k$ in the order-up-to-level system.

$$RQ_{b,k,\alpha} = \begin{cases} 
OQ_{b,k} - \max(IL_{b,k,\alpha}, 0), & IL_{b,k,\alpha} \leq ROP_{b,k} \\
0, & IL_{b,k,\alpha} > ROP_{b,k} 
\end{cases} \tag{5.5}$$

Once the replenishment quantity for biomass type $b$ in conversion facility $k$ ($RQ_{b,k,\alpha}$) is determined, the biomass supply sources should be picked to procure the calculated replenishment quantity.

- **Supplier selection**

Since biomass is dispersed over a large area, it might not be possible to procure biomass from a single supply source. Therefore, the order for biomass type $b$ will be spilled among a number of suppliers. In order to avoid empty truck transportations, the suppliers with an amount of available biomass less than one truckload would not be considered. From the remaining suppliers, the closest supplier to the conversion facility is picked. Note that biomass availability is calculated in the supplier module in Odmt. Hence, Eq. (5.6) obtained from Ross et al., (2010) is used to determine the weight of biomass type $b$ ($WT_b$), that is required to fill a truck to its maximum capacity of CA. In this equation, bulk
density \((BD_b)\) and moisture content \(\text{MC}_b\%)\) of biomass type \(b\) and the volumetric compacted expansion factor, \(VE\), are taken into account. The volumetric compacted expansion factor accounts for the increase in volume after non-chipped residues are ground into woodchips and settled due to gravity (Briggs, 2004).

\[
WT_b = CA \times \frac{BD_b}{VE} \times (1 - \text{MC}_b\%) \tag{5.6}
\]

Bulk density \((BD_b)\) is calculated using Eq. (5.7), which is obtained from (Miles & Smith, 2009) and uses the basic specific gravity of wood \((SG_{\text{basic}})\) and fiber saturation point \((\text{MC\%}_{\text{Sat}})\). Basic specific gravity of wood is its relative density with respect to a reference material, often water, at a reference temperature, typically 4 °C (Miles & Smith, 2009). Specific gravity varies significantly among species from 0.16 to 1.04 (Miles & Smith, 2009). The fiber saturation point is the moisture content above which the physical and mechanical properties of wood would not vary with moisture content (Ross, 2010). The fiber saturation point of wood averages about 30% moisture content (Miles & Smith, 2009).

\[
BD_b = \frac{SG_{\text{basic}}}{1 - 0.265 \times SG_{\text{basic}} \times (1 - \frac{\text{MC}_b\%}{\text{MC\%}_{\text{Sat}}})} \times (1 + \text{MC}_b\%) \tag{5.7}
\]

Once a biomass supply source is picked, the order information regarding the biomass type \((b)\), the number of truckloads required to transport the order from the selected supplier \(\zeta \in I\) to the destination facility \(k\) \((NT_{b,\zeta,k})\), and the quantity of item \(b\) to procure from the selected supplier \((PQ_{b,\zeta,k})\) are determined, respectively in equations (5.8) and (5.9). In Eq. (5.8), \([. ]\) denotes the floor function. Equations (5.8) and (5.9) ensure that the quantity of biomass type \(b\) that is procured from the selected supplier will form full truckloads and will not exceed the availability of biomass type \(b\) at selected supplier at state \(\alpha\) \((BA_{b,\zeta,\alpha})\).

\[
NT_{b,\zeta,k,\alpha} = \min \left( \left\lfloor \frac{BA_{b,\zeta,\alpha}}{WT_b} \right\rfloor , \max \left( \left\lfloor \frac{RQ_{b,k,\alpha}}{WT_b} \right\rfloor , 1 \right) \right) \tag{5.8}
\]

\[
PQ_{b,\zeta,k,\alpha} = NT_{b,\zeta,k,\alpha} \times WT_b \tag{5.9}
\]

In this state, the order is assigned to the selected supplier. Immediately, the replenishment quantity of item \(b\) \((RQ_{b,k,\alpha})\) and also the availability of biomass type \(b\) at the selected supplier \((BA_{b,\zeta,\alpha})\) are reduced and the on-order inventory \((OO_{b,k,\alpha})\) is increased by \(PQ_{b,\zeta,k,\alpha}\), which is the quantity of biomass type \(b\) to procure from the selected supplier \(\zeta\). Each time an order is placed, the number of times that the
conversion facility $k$ place an order for biomass type $b$ is incremented by 1 and stored in a variable called $NO_{b,k}$, which will be required to calculate the ordering costs.

The supplier selection procedure is continued until the entire replenishment quantity ($RQ_{b,k,a}$) is assigned to suppliers or until no supplier with enough biomass exists. When the latter is the case, biomass substitution will be considered.

- **Biomass substitution**

Biomass substitution is possible when the available biomass type $b$ is not sufficient to meet its demand. In this case, biomass type $b$ is substituted by a biomass type $\beta \in B$ that is acceptable by the conversion facility $k$. In the simulation model, acceptable biomass is a biomass type that has a product yield of greater than zero ($PY_{p,\beta,k} > 0$) in conversion technology $k$ for producing product $p$. The substitution procedure is similar to the supply selection procedure explained in the previous section in its general aspects. It involves selecting a supplier that has at least one truckload of biomass, determining the order information, placing the order to the selected supplier, and updating the inventory and availability variables. This procedure is repeated until the replenishment quantity ($RQ_{b,k,a}$) is ordered or no supplier exists. The major difference is that in substitution, an order can include different types of biomass that can be used instead of the original type of biomass. Therefore, a truckload can consist of different biomass types. Different biomass types have different product yields in a given conversion technology; this impacts the quantity of biomass type $\beta$ that should be procured instead of the original biomass type $b$. Equations (5.10) and (5.11) are used to determine the quantity of biomass type $\beta$ that should be procured from supplier $\zeta$ to substitute the original biomass type $b$, ($PQ_{\beta,\zeta,k,a}$), and its original type ($b$) equivalent quantity ($EQ_{\beta,b,a}$). In Eq. (5.10), $LF$ denotes the required volume to fill the remainder of truckload, which is reduced as the truck is filled; $BA_{\beta,\zeta,a}$ represents the amount of biomass type $\beta$ available at the selected supplier $\zeta$, which is calculated in the supplier’s module. $PY_{p,\beta,k}$ and $PY_{p,b,k}$ in Eq. (5.11) are the product yield of conversion technology $k$ for producing product type $p$, when using biomass type $b$ and $\beta$, respectively.

\[
PQ_{\beta,\zeta,k,a} = \text{Min} \left( LF \times BD_{\beta}, BA_{\beta,\zeta,a} \right) \tag{5.10}
\]

\[
EQ_{\beta,\zeta,b,a} = PQ_{\beta,\zeta,k,a} \times \frac{PY_{p,\beta,k}}{PY_{p,b,k}} \tag{5.11}
\]
• Receiving biomass

In the state $a$, which is when a full truck arrives and unloads at facility $k$, on-order inventory ($OO_{b,k,a}$) is reduced, while on-hand inventory ($OH_{b,k,a}$) is increased by the content of one truckload. As mentioned previously, when it comes to substitution, a truckload may contain more than one type of biomass. In this case, the equivalent quantity of the biomass types in the truckload is used to update the on-order inventory and on-hand inventory for the original biomass types. At this point, the total quantity of biomass type $b$ transported to the facility $k$ ($TQ_{b,k,a}$) is increased by the quantity of that type of biomass within the truckload.

At the end of the simulation ($NF=365$), the maximum inventory level, which is calculated based on Eq. (5.12), is set as the capacity of storage at each conversion facility $k$ denoted as $CS_k$.

$$CS_k = \text{Max} \left( d, \sum_b IL_{b,k,d} \mid d = 1,2,3,...,N = 365 \right) \tag{5.12}$$

5.3.4 Transportation module

In this module, preprocessing and transportation of biomass are modeled. The processes that are included are loading and/or chipping at the selected biomass supply source ($\zeta$), transporting biomass from the selected supplier to the conversion facility, and unloading the truck at that conversion facility. The operating hours for each of the mentioned activities are measured and recorded in this module.

The transportation cycle ($TR_{n,\zeta,k}^{\text{Cycle}}$) is determined for each truck movement ($n$) using Eq. (5.13). Transportation cycle includes the time that the truck travels empty from its location, the conversion facility, to the selected supplier’s location ($TR_{n,\zeta,k}^{\text{empty}}$), any delay at the supplier’s location ($DL_{n,\zeta,k}$), which includes the time the truck should to be fully loaded and weather related delays, the time that the truck travels full-loaded from the selected biomass supply sources to the conversion facility ($TR_{n,\zeta,k}^{\text{full}}$), and unloading time at the facility ($UL_{n,k}$). Eq. (5.14) expresses the total transportation time to the facility $k$, $TR_k^{\text{total}}$, over the simulation time horizon.

$$TR_{n,\zeta,k}^{\text{cycle}} = TR_{n,\zeta,k}^{\text{empty}} + DL_{n,\zeta,k} + TR_{n,\zeta,k}^{\text{full}} + UL_{n,k} \tag{5.13}$$

$$TR_k^{\text{total}} = \sum_{n,\zeta} TR_{n,\zeta,k}^{\text{cycle}} \tag{5.14}$$
5.3.5 Simulation model outputs

The discrete event simulation model is used to assess the total cost, demand fulfillment, and total CO\textsubscript{2} eq emission of the supply chain as follows.

- **Annual demand fulfillment**

The annual demand fulfillment ($DF_k$) ("type II service" level, and "fill rate") describes the proportion of total demand that can be fulfilled immediately from the on-hand inventory at the storage during a reference period (Snyder & Shen, 2011). Eq. (5.15) is used to calculate the demand fulfillment.

\[
DF_k = 1 - \frac{\sum_{\alpha=0}^{NF} \sum_b SH_{b,k,\alpha}}{\sum_{\alpha=0}^{NF} \sum_b DM_{b,k,\alpha}}
\]  

(5.15)

In Eq. (5.15), $SH_{b,k,\alpha}$ represents the shortage of biomass type $b$ at conversion facility $k$ in day $\alpha$, and $DM_{b,k,\alpha}$ represents the demand for raw material type $b$ at conversion facility $k$ in day $\alpha$. $NF = 365$ is the time in days that the simulation ends.

- **The total cost**

The total cost is measured by calculating the total logistics and inventory management costs for conversion facility $k$ ($Cost_k^{total}$) and is determined using Eq. (5.16). It includes total purchase ($Cost_k^{purchase}$), loading ($Cost_k^{load}$), grinding ($Cost_k^{grind}$), transportation ($Cost_k^{transport}$), and inventory ($Cost_k^{store}$) costs.

\[
Cost_k^{total} = Cost_k^{purchase} + Cost_k^{load} + Cost_k^{grind} + Cost_k^{transport} + Cost_k^{store}
\]  

(5.16)

The total purchase cost ($Cost_k^{purchase}$) is calculated in Eq. (5.17), in which $BC_b$ represents the unit cost of purchasing biomass type $b$ ($\text{$.Odmt^{-1}}$) and $TQ_{b,k}$ defines the total amount of biomass type $b$ transported to the conversion facility $k$ over the year.

\[
Cost_k^{purchase} = \sum_b BC_b \times TQ_{b,k}
\]  

(5.17)

Eq. (5.18) is used to calculate the total loading cost ($Cost_k^{load}$), considering the unit cost of loading ($\text{$.hr^{-1}}$) denoted by LC and the total loading hours for conversion facility $k$, denoted by $LD_k$.  

\[ Cost_{k}^{\text{load}} = LC \times LD_k \]  

(5.18)

The total grinding cost is expressed in (5.19), where \( GC \) is the unit cost of grinding biomass (\$/hr\(^{-1} \)) and \( GR_k \) is the total grinding hours for conversion facility \( k \).

\[ Cost_{k}^{\text{grind}} = GC \times GR_k \]  

(5.19)

The total transportation cost is obtained through Eq. (5.20), taking into account the total transportation time for conversion technology \( k \) (\( TR_k^{\text{total}} \)) and hourly transportation rate of \( C^{\text{transport}} \) (\$/hr\(^{-1} \)).

\[ Cost_{k}^{\text{transport}} = C^{\text{transport}} \times TR_k^{\text{total}} \]  

(5.20)

The total storage cost, which is calculated through Eq. (5.21), includes the fixed ordering (first term in Eq. (5.21)) (\$/order\(^{-1} \)) and biomass inventory holding costs. In Eq. (5.21), \( OC \) is unit fixed cost of ordering (\$/order\(^{-1} \)), and \( HC_{b,k} \) is the inventory holding cost of biomass type \( b \) at facility \( k \) per day (\$/Odmt\(^{-1}.\text{day}^{-1} \)). \( NO_{b,k} \) and \( OH_{b,k,a} \) are the number of orders and the on-hand inventory for biomass type \( b \) in conversion facility \( k \).

\[ Cost_{k}^{\text{store}} = OC \times \sum_b NO_{b,k} + \sum_{a=0}^{NF} \sum_b HC_{b,k} \times OH_{b,k,a} \]  

(5.21)

- **Total CO\(_2\) eq emission**

The total carbon emission from operational processes is measured in CO\(_2\) equivalent (CO\(_2\) eq). In this study, only emissions from operating the equipment for loading, grinding, and transportation are considered. The total carbon emission (\( Emission_k^{\text{total}} \)) is calculated in Eq. (5.22) for each conversion facility and includes loading (\( Emission_k^{\text{load}} \)), grinding (\( Emission_k^{\text{grind}} \)), and transportation (\( Emission_k^{\text{transport}} \)) emissions.

\[ Emission_k^{\text{total}} = Emission_k^{\text{load}} + Emission_k^{\text{grind}} + Emission_k^{\text{transport}} \]  

(5.22)

Eq. (5.23) determines the total loading emission for conversion facility \( k \). In this equation, \( LD_k \) is the total loading hour for facility \( k \), \( FC^{\text{load}} \) represents the fuel consumption of the loader per hour (l.hr\(^{-1} \)). \( EM \) is kilograms of CO\(_2\) equivalents emitted when consuming 1 litre of fuel.

\[ Emission_k^{\text{load}} = LD_k \times FC^{\text{load}} \times EM \]  

(5.23)
The total grinding emission for conversion facility $k$ is obtained through Eq. (5.24), in which $GR_k$ is the total grinding hour for conversion facility $k$ and $FC^{grind}$ is the fuel consumption of the grinder per hour (l/hr).

$$Emission_k^{grind} = GR_k \times FC^{grind} \times EM$$

(5.24)

Finally, the total transportation emission is calculated in Eq. (5.25), considering the total transportation time for conversion facility $k$ ($TR_k^{total}$) and litres of fuel consumed by the trucks when travelling for 1 hour ($FC^{transport}$).

$$Emission_k^{transport} = TR_k^{total} \times FC^{transport} \times EM$$

(5.25)

### 5.4 Assumptions and model input parameters

This section provided the parameters and assumptions that are used for running the simulation model.

#### 5.4.1 Parameters used in the supplier module

The availability of sawmill residues is estimated considering the annual biomass availability at each of sawmills, which can be found in Table 3-3 in Chapter 3 and the number of business days in each month. It is assumed that sawmills are operating continuously seven days a week.

The availability of forest residues depends on the cut-block characteristics, including the volume of standing trees, stem volumes, area, and the severity of mountain pine beetle attack which varies from one cut-block to another. A dataset that included characteristics of each individual forest cut-block was provided by FPInnovations. Table 5-1 summarizes these characteristics. Note that in estimating the recoverable residue ratio, the biodiversity considerations, e.g., soil conservation, and technical losses during handling were considered.

<table>
<thead>
<tr>
<th>Area (ha)</th>
<th>Average stem volume (m$^3$)</th>
<th>Tree volume per area (m$^3$.ha$^{-1}$)</th>
<th>Recoverable residue ratio (Odmt.m$^3$)</th>
<th>Mountain pine beetle content as a % of recoverable residue ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>(AR$_j$)</td>
<td>(VS$_j$)</td>
<td>(VH$_j$)</td>
<td>(RR$_j$)</td>
<td>(MR$_j$)</td>
</tr>
<tr>
<td>[1.80-4883.11]</td>
<td>[0.08-0.69]</td>
<td>[128.80-544.98]</td>
<td>[0.11-0.31]</td>
<td>[29%-60%]</td>
</tr>
</tbody>
</table>

Forest residues are by-products of logging activities; therefore, their availability is constrained by allowable annual cuts (AAC), which can vary in response to social, economic, environmental, and biological considerations. Table 5-2 shows the annual and seasonal variations in logged volume for years 2015, 2002, and 2006, which represent the years with the lowest, average, and highest logged...
volumes during the past 15 years. In addition to logged volume, the logging volume is also restricted
to a certain volume each month which depends on weather and soil condition. In this chapter, since
historical data are available, instead of using the AAC, the actual logged volume and monthly logging
volumes for the year 2015, corresponding to the average case are used.

Table 5-2: Annual harvest volume and its monthly distribution in three different years representing low,
average, and high availability conditions
(Collected from Harvest Billing System (Government of British Columbia, 2017a))

<table>
<thead>
<tr>
<th>Month</th>
<th>2015 (lowest)</th>
<th>2002 (average)</th>
<th>2006 (highest)</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>13.5%</td>
<td>15.4%</td>
<td>14.4%</td>
</tr>
<tr>
<td>February</td>
<td>10.6%</td>
<td>14.1%</td>
<td>13.4%</td>
</tr>
<tr>
<td>March</td>
<td>4.1%</td>
<td>7.6%</td>
<td>7.1%</td>
</tr>
<tr>
<td>April</td>
<td>0.1%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>May</td>
<td>0.8%</td>
<td>0.1%</td>
<td>0.7%</td>
</tr>
<tr>
<td>June</td>
<td>5.0%</td>
<td>6.7%</td>
<td>4.6%</td>
</tr>
<tr>
<td>July</td>
<td>12.9%</td>
<td>9.0%</td>
<td>9.1%</td>
</tr>
<tr>
<td>August</td>
<td>13.4%</td>
<td>7.6%</td>
<td>10.2%</td>
</tr>
<tr>
<td>September</td>
<td>9.4%</td>
<td>6.6%</td>
<td>7.8%</td>
</tr>
<tr>
<td>October</td>
<td>10.3%</td>
<td>11.5%</td>
<td>11.0%</td>
</tr>
<tr>
<td>November</td>
<td>9.9%</td>
<td>10.2%</td>
<td>11.4%</td>
</tr>
<tr>
<td>December</td>
<td>10.0%</td>
<td>11.2%</td>
<td>10.3%</td>
</tr>
</tbody>
</table>

Logged volume (m$^3$) | 1,026,715.48 | 2,856,338.04 | 4,751,674.763

Moreover, the biomass supply time depends on the availability and productivity of machinery.
Machines perform differently in different forest areas as they have different characteristics, e.g., volume
per stem of trees. In order to account for the impact of availability and productivity of machinery on
biomass availability, the productivity of machinery was considered as a function of stand
characteristics. Data related to machinery and equipment are summarized in Table 5-3.
Table 5-3: Productivity, cost and fuel consumption of machinery and equipment

<table>
<thead>
<tr>
<th>Operation</th>
<th>Type of equipment</th>
<th>Power (kW)</th>
<th>Productivity/ payload</th>
<th>Cost</th>
<th>Fuel Consumption</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Felling</td>
<td>Feller-buncher</td>
<td>149</td>
<td>173.02×(Stem volume)⁰.⁷₄₆⁴ (m³.h⁻¹) c</td>
<td>155²</td>
<td>30-47 g</td>
<td>29</td>
</tr>
<tr>
<td>Skidding</td>
<td>Grapple skidder</td>
<td>95</td>
<td>-48.05×Ln(Skidding distance)+312.91 (m³.h⁻¹) c</td>
<td>105²</td>
<td>20-30 g</td>
<td>29</td>
</tr>
<tr>
<td>Delimbing</td>
<td>Dangle-head processor</td>
<td>126</td>
<td>85.131×(Stem volume)⁰.⁷₃₇ (m³.h⁻¹) c</td>
<td>130 ³</td>
<td>22-25 g</td>
<td>58</td>
</tr>
<tr>
<td>Loading</td>
<td>Loader</td>
<td>146</td>
<td>120 -170 (m³.h⁻¹) d</td>
<td>105.54²</td>
<td>13 b</td>
<td></td>
</tr>
<tr>
<td>Grinding</td>
<td>Horizontal grinder</td>
<td>600</td>
<td>14.82 (Odmt. h⁻¹) b</td>
<td>409.49²</td>
<td>135 b</td>
<td></td>
</tr>
<tr>
<td>Transporting</td>
<td>Self unloading semi-trailer chip van</td>
<td>352</td>
<td>113 m³ e</td>
<td>124.28 f</td>
<td>0.68 g</td>
<td></td>
</tr>
<tr>
<td>Unloading</td>
<td>-</td>
<td>352</td>
<td>Uniform [45,75] minutes f</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Storage</td>
<td>Fabric on frame storage</td>
<td>-</td>
<td>Biomass carrying cost: 0.07 ($/Odmt⁻¹.day⁻¹) derived from f</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

5.4.2 Parameters used in the conversion facility module

- **Biomass demand**

The monthly demand for each type of biomass at each facility is obtained from the optimization model developed in Chapter 3. The monthly demand was disaggregated to daily values considering the number of days in each month and assuming that the conversion facilities are operating seven days a week. The ranges of daily demand for each type of biomass at each conversion facility are presented in Table 5-4.

Table 5-4: Daily demand for each type of biomass at each conversion facility

<table>
<thead>
<tr>
<th>Biomass type</th>
<th>Location B</th>
<th>Location A</th>
<th>Location C</th>
<th>Location A</th>
<th>Location C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power Plant</td>
<td>[0.5 MW]</td>
<td>[0.47]</td>
<td>[0-23]</td>
<td>-</td>
<td>[0-393]</td>
</tr>
<tr>
<td>CHP plant</td>
<td>[45,000 tonne.year⁻¹]</td>
<td>-</td>
<td>[61,147]</td>
<td>[194-391]</td>
<td></td>
</tr>
<tr>
<td>CHP plant</td>
<td>[2,45]</td>
<td>[0.9]</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Pellet plant</td>
<td>-</td>
<td>-</td>
<td>[0.72]</td>
<td>[0-120]</td>
<td></td>
</tr>
<tr>
<td>Pyrolysis plant</td>
<td>-</td>
<td>[2.45]</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

*The capacity of the pyrolysis facility is expressed based on its biomass input capacity. The capacity for the rest of the facilities is based on their output products.*

5.5 Results and analyses

The simulation model was programmed in the Java language using AnyLogic® (The AnyLogic Company, 2017). The model was run for a one-year planning horizon with a 2-week warming period. The considered inventory control systems are summarized in Table 5-5. The inventory parameters, reorder point and order quantity, were selected based on the trial and error simulation runs to get acceptable demand fulfillment rates for all the conversion facilities.

Table 5-5: Alternative inventory policies and the inventory control parameters for each system

<table>
<thead>
<tr>
<th>Inventory system</th>
<th>Reorder point</th>
<th>Order quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order-up-to-level</td>
<td>14 days of demand</td>
<td>Up to 28 days of demand</td>
</tr>
<tr>
<td>Fixed order quantity</td>
<td>14 days of demand</td>
<td>28 days of demand</td>
</tr>
</tbody>
</table>

In order to obtain the 95% confidence interval considering an allowable error of 5% for the estimate of the mean for all the performance measures, the simulation model was run for 50 replications. For each
replication, the same initial conditions (zero initial inventories at supply sources and conversion facilities) were assumed. Each replication took 22 seconds to finish.

In order to compare the performance measures of the two inventory systems, the 2-sample t-test was used (Ott & Longnecker, 2015). Since the samples from the two inventory systems were not related, the assumption about independent samples held true. Additionally, for both inventory management systems, the sample size (50 runs) was large enough (> 30), therefore, according to the Central Limit Theorem (Ott & Longnecker, 2015), the assumption regarding the normal distribution of sample means held true. The F-test was used to check if the populations had equal variances or not. In the case of equal variances, the 2-sample t-test using pooled variances was used, whereas, in the case of unequal variances, the 2-sample t-test using separate variances was performed. The detailed formulae for the 2-sample t-test procedure can be found in any statistical analysis textbook, such as the one by Ott & Longnecker (2015).

5.5.1 Number of resources

The number of machinery is one of the required inputs of the simulation model. However, the number of resources was estimated by running 50 iterations of the simulation model with an unlimited number of resources, i.e., loader, grinder, truck, and unload deck, for the fixed order quantity system. Then, the number of machines were estimated using the operating times obtained from the simulation model. Table 5-6 demonstrates the estimated number of machinery required for each location.

<table>
<thead>
<tr>
<th>Location</th>
<th>Number of machines required</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Loader</td>
<td>Grinder</td>
<td>Truck</td>
<td>Unload deck</td>
</tr>
<tr>
<td>Location A</td>
<td>11</td>
<td>11</td>
<td>40</td>
<td>4</td>
</tr>
<tr>
<td>Location B</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Location C</td>
<td>30</td>
<td>30</td>
<td>99</td>
<td>8</td>
</tr>
</tbody>
</table>

For comparing the alternative inventory systems, the same number of pieces of equipment was considered, and the inventory systems were compared with respect to their required operating hours for each operation. Based on the results, the fixed order quantity system would require more operating hours, compared with the order-up-to-level system. Depending on the conversion facility, the annual operating hours are higher up to 14% for loading/grinding, 54% for transporting, and 36% for unloading activities in the fixed order system compared with the up-to-order level system. The reason, as will be explained below, is that in general more amount of biomass would be transported to the facilities in the fixed order quantity inventory system.
5.5.2 Biomass transportation quantities and inventory levels

In general, the total amount of biomass to transport to a conversion facility depends on the order quantity and the number of orders per year.

Based on the results for the case study, in the fixed order quantity system compared with the order-up-to-level system, on average 2-6% more biomass would be transported to the facilities over the year, and as it is shown in

Table 5-7, 17-70% more biomass would be stored daily at the facilities. This is because the order quantity is higher in the fixed order quantity system than that in the order-up-to-level system. Even though biomass availability is restricted and the entire order quantity may not be received by facilities, compared with the order-up-to-level system, generally more biomass is received per order in the fixed order quantity system. For a given reorder point, higher order quantity reduces the ordering frequency as the reorder point would be reached slower. As an instance, the pellet plant in Location A would place 300 orders per year and receive an average quantity of 166 Odmt biomass per order (300×166=49,800 Odmt over the year) under the order-up-to-level system. Under the fixed order quantity system, the same facility would place 292 orders per year and receive on average 175 Odmt of biomass per order (292×175=51,100 Odmt over the year). Although the number of orders in the fixed order quantity inventory system is lower, the order cycle (the time between orders) in this system does not differ considerably from that in the order-up-to level system. For instance, the order cycle is 1.21 days in the order-up-to-level system and 1.25 days in the fixed order quantity system for the pellet plant in Location A. Therefore, daily inventory levels and the amount of biomass transported to the facilities over the year are in general higher in the fixed-order-quantity system.

Table 5-7: Average on-hand inventory for inventory management systems

<table>
<thead>
<tr>
<th>Conversion facility</th>
<th>Average daily biomass inventory (Odmt.day⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Order-up-to-level</td>
</tr>
<tr>
<td>0.5 MW power plant – Location B</td>
<td>84</td>
</tr>
<tr>
<td>1 MW CHP plant – Location C</td>
<td>240</td>
</tr>
<tr>
<td>2 MW CHP plant – Location A</td>
<td>1,153</td>
</tr>
<tr>
<td>45,000 tonne.year⁻¹ pellet plant – Location A</td>
<td>2,696</td>
</tr>
<tr>
<td>600 Odmt.day⁻¹ pyrolysis plant – Location C</td>
<td>9,177</td>
</tr>
</tbody>
</table>
### 5.5.3 Annual demand fulfillment

Figure 5.3 illustrates the annual biomass demand fulfillment of the conversion facilities for the order-up-to-level and fixed order quantity inventory management systems.

![Comparison of annual demand fulfillment of facilities in the two inventory management systems](image)

As shown in Figure 5.3, high demand fulfillment ($DF \geq 90\%$) is achieved for all the conversion facilities for both inventory management systems. Considering the significance level of 0.05, the fixed order quantity system has better demand fulfillment for all the conversion facilities. The superior service level of the fixed order quantity is explainable by the higher quantity of biomass that would be stored at conversion facilities compared with the order-up-to-level system (shown in Table 5-7). Since more biomass would be stored at the facilities in the fixed order quantity system, biomass shortage would occur less frequently.

### 5.5.4 Total cost and total CO$_2$ eq emission

The total cost and the total CO$_2$ eq emission of inventory systems are compared in Figure 5.4 for bioenergy and in Figure 5.5 for biofuel facilities.

The slightly better demand fulfillment in the fixed order quantity would result in a higher cost. Depending on the conversion facility, the annual total cost could be 11\% to 34\% more expensive for the fixed order quantity inventory system. As already stated, more biomass would be transported and stored at the conversion facilities in the fixed order quantity system, compared with the order-up-to-level system, which led to higher handling and storage requirements in the fixed order quantity system.
Since the demand fulfillment rates are not exactly the same for the two inventory systems, a general conclusion cannot be made regarding the economic performance of the systems. However, for a conversion facility that has a demand fulfillment of 100% in both inventory systems, such as the 2 MW CHP plant in Location A, the total cost for fixed order quantity system is 30% higher than that of the order-up-to-level system. In general, the demand fulfillment rates would not be more than 2% higher,
while costs could be up to 34% more expensive for the fixed order quantity system compared with the order up-to-level system.

Depending on the type of conversion facility, the transportation has the largest contribution in total cost ranging from 50% to 82%, followed by, respectively, grinding (11%-32%), loading (3%-8%), storage (2%-7%), and biomass purchase (1%-5%) costs in both inventory management system.

The order-up-to-level inventory system seems to be advantageous with respect to the total CO$_2$ eq emission as well for all the conversion facilities in the supply chain network (Figure 5.4 and Figure 5.5). The total CO$_2$ eq emission was calculated as a function of operating hours, which were greater in the fixed order quantity system.

Depending on the conversion facility, the grinding contributes the most (56%-81%) to the total CO$_2$ eq emission. Transportation follows the grinding by contributing 11% to 36% of emissions. Loading had a share of 6% to 8%.

### 5.5.5 Scenario analysis

In this section, the impact of the changes in inventory control parameters on the outputs of the simulation model is analyzed for alternative inventory management systems. Herein, the variations in reorder point and reorder quantity, are investigated separately using scenario analysis as follows. For the sake of brevity, the results are discussed for only one of the conversion facilities, the 45,000 tonnes.year$^{-1}$ pellet plant in Location A. However, it will be argued if the conclusions are similar for the rest of the conversion facilities or not and the reasons will be justified.

- **Impact of order quantity**

The simulation model was run for scenarios illustrated in Table 5-8. Note that while the reorder point is fixed, the order quantity increases over the scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>Base Case</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reorder point (days of biomass demand)</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>Order quantity (days of biomass demand)</td>
<td>21</td>
<td>28</td>
<td>35</td>
<td>48</td>
</tr>
</tbody>
</table>

The impact of changing order quantity on the performance of the two inventory systems is illustrated for cost and demand fulfillment in Figure 5.6 and for the total CO$_2$ eq emission in Figure 5.7. For the 45,000 tonnes.year$^{-1}$ pellet mill, the fixed order quantity inventory system has slightly a better demand...
fulfillment, but a higher total cost (Figure 5.6) and higher total CO₂ eq emission (Figure 5.7) in all the scenarios. The same results are observed for the rest of the conversion facilities.

Figure 5.6: Changes in the total cost and annual demand fulfillment with the increase in order quantity for 45,000 tonnes.year⁻¹ pellet plant in Location A

Figure 5.7: Changes in the total CO₂ eq emission with the increase in order quantity for 45,000 tonnes.year⁻¹ pellet plant in Location A

Based on the results, for both inventory management systems, when the order quantity is increased, more biomass would be transported to the plant (without being necessarily needed). As a result, the costs and emissions would increase without any significant change in demand fulfillment. However, this conclusion is not precisely true for all the scenarios. As an instance, for the 45,000 tonnes.year⁻¹
pellet mill, when increasing the order quantity from 35 to 42 days of biomass demand in the order-up-to-level system (Figure 5.7), unlike expected, the total CO₂ eq emission decreases. This is because in this case, some amount of sawmill woodchips would be procured from Location B to substitute mountain pine beetle residues, which would not available in sufficient amounts to fulfill the order quantity. Since sawmill residues do not require grinding and considering that the fuel consumption for grinding is considerably high, the savings in the total CO₂ eq emission resulting from eliminating the grinding operation exceed the increased CO₂ eq emissions resulting from increased transportation distances. In spite of savings in grinding costs, the increased transportation costs overweigh the savings in grinding costs.

- **Impact of reorder point**

The scenarios illustrated in Table 5-9 were considered to assess the impact of changing reorder point. Herein, the order quantity is fixed, while the reorder point increases over scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>Base Case</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reorder point (days of biomass demand)</td>
<td>7</td>
<td>14</td>
<td>21</td>
</tr>
<tr>
<td>Order quantity (days of biomass demand)</td>
<td>28</td>
<td>28</td>
<td>28</td>
</tr>
</tbody>
</table>

The impact of changing the order quantity on the performance of inventory systems is illustrated for the total cost and annual demand fulfillment in Figure 5.8 and for the total CO₂ eq emission in Figure 5.9.
Figure 5.8: Changes in total cost and annual demand fulfillment with the increase in the reorder point for 45,000 tonnes.year\(^{-1}\) pellet plant in Location A

Figure 5.9: Changes in total CO\(_2\) eq emission with the increase in reorder point for 45,000 tonnes.year\(^{-1}\) pellet plant in Location A

In general, for higher reorder points, the conversion facility would have a higher amount of biomass on-hand when placing an order to the suppliers. Therefore, the risk of biomass shortage during the lead-time, i.e., the length of the time between placing an order and its receipt, reduces. Consequently, the demand fulfillment should improve. The improvement in demand fulfillment with the increase in reorder point is observed for all the conversion facilities and for both inventory management systems.
For the fixed order quantity inventory system, with the increase in reorder point, the total cost, and total emission increase. For this inventory system, increasing the reorder point would increase the frequency of ordering, while the order quantity remains the same; therefore, over a year, more biomass would be transported and consequently, the cost and the emission would increase. This conclusion does not hold true for the order-up-to level inventory system. In this system, for a given target level, with the increase in the reorder point, the order quantity decreases while the ordering frequency increases. With the decrease in order quantity, the transportation cycle would decrease because the distances for biomass procurement and the waiting times for loading the trucks at the supply sources would reduce.

5.6 Summary and conclusions

In this chapter, the biomass inventory management was addressed taking into account the impact of supply chain complexities in evaluating and comparing the performance of two continuous inventory systems: 1) order-up-to-level, and 2) fixed order quantity. To achieve this objective, a discrete event simulation model was developed and the data related to a case study in British Columbia was used to run the simulation model.

The results showed that the selection of the inventory management system impacted the annual demand fulfillment slightly, but affected considerably the total cost and the total CO₂ eq emissions of the supply chain. For the given case study, the fixed order quantity system showed up to 2% higher demand fulfillment. However, this slightly better demand fulfillment was achieved through storing 17% more biomass, which increased the operating hours required for biomass preprocessing and transportation by up to 50% and consequently increased the total cost by up to 34% and the total CO₂ eq emission by up to 14%. Additionally, the results of scenario analysis emphasized that a slight improvement in demand fulfillment for each individual inventory system would require considerable expenditure on operating hours and would result in increased emission. Hence, the selection of a proper inventory management system offers the possibility to reduce logistics costs and emissions, which is a determining factor in enhancing the competitiveness of biomass as a replacement for fossil fuels.

The simulation model in this chapter included the upstream activities of the supply chain and therefore the performance of the supply chain was estimated based on the total cost including biomass purchase, preprocessing, transportation, and storage costs for one year. In the next chapter, the model is extended to include the midstream and downstream activities of the supply chain over the service life of the project. Additionally, the simulation model is coupled with the integrated strategic and tactical model developed in Chapter 3.
Chapter 6. Integrated strategic, tactical and operational planning of a forest-based biomass supply chain - A Hybrid optimization-simulation approach

6.1 Synopsis

In this chapter, a hybrid optimization-simulation approach is proposed to solve the supply chain design problem considering variations at the operational level. In this approach, the strategic supply chain design and the flow of biomass from biomass supply sources to each facility at the tactical level are determined by solving the integrated strategic and tactical model developed in Chapter 3. The net present value (NPV) and annual demand fulfillment of the prescribed design are then evaluated using an extended version of the discrete event simulation model proposed in Chapter 5, considering variations across the supply chain, interdependencies among various stages of the supply chain, and the operational level constraints, e.g., availability of logistical resources including trucks, loader, and grinders and their productivity. The demand fulfillment of the facilities for each design is improved to an acceptable level through running the simulation and the tactical version of the optimization models iteratively. This procedure is repeated until a design with the best NPV is obtained. Hereinafter, the procedure to build the connection between the optimization and the simulation models is explained. The results are analyzed, and eventually concluding remarks are presented.

6.2 Hybrid optimization-simulation approach

The solution procedure developed in this chapter is based on a generalized solution methodology proposed by Acar, Kadipasaoglu and Day (2009) to solve various combinatorial problems with components of uncertainty. The solution procedure in (Acar et al., 2009) included a mixed integer linear programming (MILP) model to obtain the optimal solution to a deterministic facility location problem. Then, the Monte Carlo simulation modeling was used to determine the impact of uncertainty on the objective function value of the deterministic solution. The difference between the deterministic and simulated objective functions was used as feedback to the MILP model, which searched for a new solution taking into account the impact of variations on the objective of previously found solutions. The process iterated until a previously simulated solution with uncertainty impact was found to be optimal in the current run of the MILP model. One key strength of the hybrid optimization-simulation solution procedure proposed by (Acar et al., 2009) is in its capability to achieve a global optimal solution (Figueira & Almada-Lobo 2014). However, it is geared to discrete solution spaces (Figueira & Almada-Lobo, 2014).

The hybrid optimization simulation model proposed in this chapter is similar to the solution procedure developed in (Acar et al., 2009) in its general aspects; the hybrid approach herein is an iterative
procedure in which the simulation model is run following the optimization model. The simulation model evaluates each solution generated by the optimization model considering more realistic conditions and corrects the objective function for that particular solution.

The hybrid approach proposed in this chapter differs from the solution procedure developed by Acar et al. (2009) in several ways. In the hybrid approach proposed by Acar et al. (2009), the MILP model is resolved in each iteration. Therefore, this approach might be very time-consuming for the models with long solution times. Unlike the hybrid model proposed by Acar et al. (2009), the MILP component of the hybrid scheme in this chapter is solved only once in an initial step where a pool of alternative solutions is obtained. Moreover, unlike the hybrid approach in Acar et al. (2009), the hybrid scheme proposed in this chapter allows for adjusting the tactical plans (presented as continuous variables) for each solution generated by the optimization model. This is done by building a linkage between the simulation model and a tactical level optimization model. The proposed hybrid optimization simulation in this chapter is explained below in detail.

The proposed hybrid scheme has three stages, which are (1) solution pool generation, (2) solution evaluation, and (3) solution improvement. Figure 6.1 illustrates the flowchart of the hybrid optimization and simulation approach.

6.2.1 Solution pool generation

In the first stage, the solution generation stage, the integrated strategic and tactical model developed in Chapter 3 is run to obtain a solution pool containing alternative designs with a positive net present value ($NPV > 0$). The generated solutions differ in their strategic design, i.e. location, size, and type of conversion technologies. Generating the solution pool is achieved using the populate method of the CPLEX solver from IBM ILOG (IBM Knowledge Center, 2017). The populate method works in two steps. Initially, it solves the model to optimality, while setting up a branch and cut tree for the next step (IBM Knowledge Center, 2017). Using the information stored in the first step, the populate method continues with exploring the tree and generating multiple integer feasible solutions (IBM Knowledge Center, 2017). The solutions are then ranked based on their $NPV$ in a descending order. Therefore, the first and last solutions are the designs that are expected to achieve, respectively, the highest and the lowest profit. The NPV of each of the generated solutions from the optimization model is called $NPV^{opt}$. 
6.2.2 Solution evaluation

The solution evaluation stage starts with retrieving the first solution from the solution pool that has not been evaluated yet. In this stage, the current solution is evaluated by running an extended version of the simulation model that was proposed in Chapter 5. The modifications to the simulation model are explained in detail later in Section 6.2.4. For each solution, the strategic design of supply chain, i.e., location, type and capacity of conversion facilities, as well as selected biomass suppliers, and the optimal tactical plans, i.e., optimal flow and inventory levels of biomass and products, are used as the
inputs of the simulation model. Note that the optimal tactical plans are used as targets. Since in the simulation model, the variations at the operational level are taken into account, it might not be possible to achieve optimal tactical plans (targets). For instance, for a given month, the optimal amount of biomass to transport prescribed by the optimization model might not be achieved because of variations in biomass supply availability. As a result, the optimal storage quantity obtained from the optimization model cannot be formed. This leads to biomass shortages, resulting in lower production level and product distribution quantities compared with their optimal values. Hence, the net present value obtained from the simulation model, called $NPV^{\text{sim}}$, differs from the optimal value ($NPV^{\text{opt}}$). In this stage, the $NPV^{\text{sim}}$ and the monthly shortage for each type of biomass are recorded.

6.2.3 Solution improvement

In the third stage, the feedback from the previous iteration is used to improve the performance of the solution. The tactical optimization model is a modified version of the integrated strategic and tactical model that was developed in Chapter 3, in which the long term decisions related to the design of the supply chain are considered to be fixed. The tactical model is used in the solution improvement stage to allow for adjusting the plans at the tactical level based on the feedback that it receives from the simulation model in an iterative manner. The adjustment can be procuring more amount of biomass or producing less amount of products to reduce the biomass demand and is done by adding the biomass shortage to the right-hand side of the inventory balance constraint (3.33) as expressed in Eq. (6.1).

$$
(1 - SL) \times z_{b, l, t}^{t+\lambda \times (T-t) - (1-\lambda)s - \lambda} + \sum_{t} o_{b, k, l}^{t, s} = \sum_{b} \sum_{k} \sum_{t} \sum_{s} \sum_{l} DM_{b, k, l}^{t, s} - n_{b, k, l}^{t, s} + z_{b, l}^{t, s} + \sum_{k} DF_{b, k, l}^{t, s}
$$

\begin{align}
\lambda &= 1 & \text{if } t = 1 \\
\lambda &= 0 & \text{Otherwise}
\end{align}

(6.1)

where the parameter $DM_{b, k, l}^{t, s}$ expresses the demand and biomass type $b$ in conversion technology $k$ in location $l$ in month $t$ in year $s$. In each iteration ($r$), the value for $DM_{b, k, l}^{t, s}$ is set to the optimal value for the decision variable $u_{b, k, l}^{t, s}$ prescribed by either the integrated strategic and tactical or the tactical optimization models in the previous iterations. For each design, the tactical model is called for the first time in the second iteration. Therefore, the parameter $DM_{b, k, l}^{t, s}$ takes its value based on $u_{b, k, l}^{t, s}$ prescribed by the integrated strategic and tactical model only in the first iteration. In the next iterations, the optimal value for $u_{b, k, l}^{t, s}$ obtained from the tactical model in the iteration before is used to initialize the parameter $DM_{b, k, l}^{t, s}$. 

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In Eq (6.1), $n_{b,k,l}^{ts}$ is a non-negative decision variable, denoting a portion of demand to leave unmet and the parameter $UF_{b,k,l}^{ts}$ represents shortage for type $b$ in conversion technology $k$ in location $l$ in month $t$ in year $s$. The parameter $UF_{b,k,l}^{ts}$ is determined through Eq. (6.2).

$$UF_{b,k,l}^{ts} = \max( DM_{b,k,l}^{ts}, \sum_r SH_{b,k,l}^{ts,r-1} ) \quad \forall b \in B \ l \in L \ s \in S \ t \in T$$

(6.2)

$SH_{b,k,l}^{ts,r}$ is obtained from the simulation model and denotes the shortage of biomass type $b$ in technology $k$ in location $l$ in month $t$ of year $s$, in iteration $r$. Adding the parameter $UF_{b,k,l}^{ts}$ to the right-hand side of constraint induces additional demand which forces the model to prescribe more amount of biomass to transport and to store while including $n_{b,k,l}^{ts}$ in this constraint allows for the possibility to reduce the consumption amount of one type of biomass, if more economical.

A new constraint expressed in Eq. (6.3) is added to link the biomass consumption and the demand. Additionally, this constraint provides a linkage to operating capacity constraint (3.27) which guarantees the minimum operating capacity even if a portion of demand is left unmet.

$$u_{b,k,l}^{ts} = DM_{b,k,l}^{ts} - n_{b,k,l}^{ts}$$

(6.3)

Once the tactical plans are adjusted, they should be re-evaluated by the simulation model again. The solution improvement and solution evaluation stages are run iteratively until the percentage difference between the net present values ($NPV_{sim}$) from two consecutive iterations is within $\varepsilon=1\%$ adopted from a study by Sahay & Ierapetritou (2014). Once this stopping criterion is met, the net present value of the current solution is set to the net present value obtained in the last iteration of the hybrid model.

The next step is then to check whether there is a need to evaluate another supply chain design from the solution pool or not. To do this, the $NPV_{sim}$ of each of evaluated solutions is compared with the deterministic net present value of the next design in the solution pool that has not been evaluated yet.

If the NPV that is obtained from the integrated strategic and tactical optimization model for the next design is higher than the NPV of the all the evaluated supply chain designs, the hybrid approach begins from the second stage. Otherwise, the best design will be the design among all the evaluated solutions that has the highest $NPV_{sim}$. In order to draw this conclusion, it is necessary to assume that for each solution the $NPV_{sim}$ is lower than the $NPV_{opt}$. 

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6.2.4 Modifications in the simulation model

As mentioned previously, the hybrid approach uses an extended version of the simulation model developed in Chapter 5. The simulation model proposed in Chapter 5 included the upstream logistics, which refers to transport, storage, and delivery of biomass to the conversion facilities, and biomass storage at conversion facilities. Therefore, only the total upstream logistics cost was estimated in the simulation model. Whereas, the optimization model proposed in Chapter 3 included the upstream as well as the downstream logistics, which deal with storage and distribution of products to the customers. Additionally, the objective function of the optimization model was to maximize the net present value of the supply chain. Because of these differences, the simulation model needs to be extended to include the downstream logistics of the supply chain, additional functions to calculate conversion and downstream logistics costs, as well as revenues to facilitate the interaction between the simulation and optimization models. The modifications and changes in the simulation model are explained for each module as follows.

- **Supplier module**
  
  In the supplier module, instead of considering all the forest cut-blocks, only the cut-blocks that are prescribed by the optimization model are considered for logging. Since a fewer number of cut-blocks are considered, the annual allowable cut (AAC) is apportioned to restrict the total volume that is logged annually.

  Additionally, the required time for moving equipment and machinery from one cut-block to another one is accounted for. This time is calculated taking into account the Euclidean distance between the cut-blocks and a speed of 5 km per hour for moving the logging equipment. This speed is adopted from (Sessions et al., 2013), in which the interactions between chipping and trucking were accounted for in evaluating logistics costs of a forest-based supply chain in Oregon, US. Additionally, a restriction is added to limit the number of trucks that can wait simultaneously at the roadside to 5.

- **Conversion facilities module**
  
  A number of modifications are made in the existing procedures of the model and new procedures are introduced.

  **Inventory control**

  The main change in this procedure is that instead of using any of the fixed order or up-to-order level inventory management systems, a general rule is used. This is because ordering based on those inventory management systems is subjective to inventory control parameters, i.e., order quantity and
order point. The inventory control parameters used in Chapter 5 were evaluated for the base case design and may not be suitable for the alternative supply chain designs. To be able to compare the designs without worrying about the impact of these parameters the following rule is used. The replenishment quantity for each type of biomass is updated at the beginning of each month to the optimal value for that biomass type to transport from biomass supply sources to each facility location which is obtained from the optimization model.

Due to variations at the operational level, it may not be possible to transport the amount of biomass that is prescribed by the optimization model in full amounts or on-time. Depending on the inventory position (on-hand inventory + on-order inventory) and the optimal ending inventory level of the previous month, the replenishment quantity is adjusted. The replenishment quantity is decreased if the inventory position is more than the optimal inventory level suggested by the optimization model and increased if the inventory position is less than what it should be ideally. Once the replenishment quantity is defined, the biomass supply selection procedure is implemented as explained in Section 5.3.3 of Chapter 5 until the entire order quantity is fulfilled or until no more biomass is available.

**Biomass substitution**

In the previous chapter, when the available amount of one biomass type was not sufficient to fulfill the entire replenishment quantity calculated for that type, the substitution procedure was implemented to order other types of biomass that could be used instead of the original biomass type. The substitution procedure at the ordering stage worked well in the previous chapter, in which the simulation model was run for 1 year.

One drawback with biomass substitution at the ordering stage is that it may deteriorate the demand fulfillment of other types of biomass. This drawback became relevant when the model was run for 20 years for the first time. This is because the availability of biomass from cut-blocks, particularly mountain pine residues, decreases over time. This led to ordering more amount of forest residues to replace mountain pine beetle residues such that enough forest residues would not be available to meet its own demand. In the current chapter, this drawback is overcome by substituting biomass from on-hand inventory at the conversion facilities and considering priorities. The substitution procedure is implemented in the production procedure as follows.

- **Production procedure**

This procedure is a new addition to the simulation model, in which the production quantity for each type of product at each location is estimated on a daily basis. The fixed and variable operating costs are also estimated. The main input for this procedure is the daily demand for each biomass type in the
selected conversion technology at each facility location. The value for this parameter is updated at the beginning of each month by reading the optimal values for the amount of biomass type \( b \) to use in conversion technology \( k \) in facility location \( l \) in month \( t \) of year \( s \) from the Excel file and dividing it by the number of days in the corresponding month.

Then, if for any biomass type there is not enough biomass on-hand to meet its demand, the biomass substitution procedure is implemented. In this procedure, the other biomass types that are available in the storage in surplus amounts are considered for the substitution and ranked based on their product yield in the corresponding technology in descending order. The biomass with the highest product yield is picked for substitution.

In order to avoid future shortages for the biomass type that was used for substitution, their replenishment quantity is increased by the amounts that are used for substitution. Additionally, the shortage amount for the original biomass shortage is reduced by an adjusted amount based on the product yields.

The substitution procedure is continued until the shortage reaches to zero or no more substitutable biomass is available in the inventory.

- **Product distribution and storage**

In this new procedure, the daily quantity of each type of product that should be distributed among different supply chain entities, as well as product distribution and storage costs are defined.

Bioenergy products, if produced, can be used for meeting the energy demand of sawmills and the conversion technology. Any surplus amount is assumed for selling to the local grid. The optimization model prescribes the quantity of products that should be used by each supply chain entity. However, because of the existing variations at the operational level, it might not be possible to produce the prescribed amount; whenever this is the case, the priority is to meet the sawmill energy demand. After bioenergy products are allocated to sawmills, if any amount is left, it is considered for meeting the energy demand of prescribed conversion technologies at each location. After allocation of energy products to the sawmill and the conversion facilities at each location is done, the surplus bioenergy product, if available, would be sold to the local grid.

Biofuel products once produced should be first transferred to the product storage facility. Then, the daily demand of the products in their markets would be met from the product inventory. The daily demand for each product in each market is updated at the beginning of each month by reading the amount of each product type to distribute from each facility location to each market in each month from the Excel file and dividing it by 30 (the number of days in a month).
• Simulation model outputs

For each month \((t)\) of each year \((s)\), biomass shortage \((SH_{b,k,l}^{ts})\) is calculated for each type of biomass, \(b\), and for each of the conversion facility \((k)\) prescribed by the optimization model for operation at each location \((l)\) based on the daily biomass shortage \((SH_{b,k,l}^{d,ts})\) which is estimated in the production procedure. This output of the simulation model is used as an input to the optimization model in the improvement stage.

\(NPV_{sim}\) is the other output of interest. \(NPV_{sim}\) is calculated using Eq. (3.1) in Chapter 3. In order to calculate the \(NPV_{sim}\), transportation, loading, grinding costs that are estimated based on their operating times using respectively equations (5.18), (5.19), and (5.20) in Chapter 5. Biomass storage is calculated considering Eq. (5.21). Other components of \(NPV_{sim}\) are calculated in the same way they were calculated in Chapter 3. Note that the decision variables in these equations are replaced with their corresponding values as estimated by the simulation model.

6.3 Results and analyses

6.3.1 Alternative supply chain designs

Overall, 43 solutions with positive NPV were obtained from the solution generation stage. The \(NPV_{opt}\) of these solution ranged from $60,821,666 to $0.00, which corresponds to making no investment at all. The set of generated solutions included a wide variety of investment combinations in bioenergy and/or biofuel technology. For the sake of brevity, only 12 solutions that were used in the hybrid approach before meeting the stopping criterion are shown here. These solutions are listed in Table 6-1 in descending order with respect to their NPV.

Obtaining the overall optimal supply chain design considering the variation at the operational level involved evaluating and improving supply chain designs 1 to 12 presented in Table 6-1. In the following sections, the results of solution evaluation and solution improvement for the supply chain of the first design is explained in detail.

6.3.2 Performance evaluation of the base case design

The solution procedure starts with evaluating the supply chain design with the highest net present value. The simulation model is run for the first design, the one that was initially proposed by the integrated strategic and tactical model in Chapter 3. The performance of this supply chain design in terms of biomass demand fulfillment and net present value are discussed.
Table 6-1: Alternative supply chain designs obtained in the solution generation stage and ranked in descending order with respect to their NPV

<table>
<thead>
<tr>
<th>Design</th>
<th>Location A</th>
<th>Location B</th>
<th>Location C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (45,000 tonnes.year⁻¹)</td>
<td>Biomass gasifier + ICE -Power only (0.5 MW)</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pyrolysis plant (600 odmt.day⁻¹)</td>
</tr>
<tr>
<td>2</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (45,000 tonnes.year⁻¹)</td>
<td>No technology was recommended</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pyrolysis plant (600 odmt.day⁻¹)</td>
</tr>
<tr>
<td>3</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pellet plant (15,000 tonnes.year⁻¹)</td>
<td>Biomass gasifier + ICE , Power only (0.5 MW)</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pyrolysis plant (600 odmt.day⁻¹)</td>
</tr>
<tr>
<td>4</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pellet plant (15,000 tonnes.year⁻¹)</td>
<td>No technology was recommended</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pyrolysis plant (600 odmt.day⁻¹)</td>
</tr>
<tr>
<td>5</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (45,000 tonnes.year⁻¹)</td>
<td>Biomass gasifier + ICE , Power only (0.5 MW)</td>
<td>Pyrolysis plant (600 odmt.day⁻¹)</td>
</tr>
<tr>
<td>6</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (45,000 tonnes.year⁻¹)</td>
<td>No technology was recommended</td>
<td>Pyrolysis plant (600 odmt.day⁻¹)</td>
</tr>
<tr>
<td>7</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pellet plant (15,000 tonnes.year⁻¹)</td>
<td>No technology was recommended</td>
<td>Pyrolysis plant (600 odmt.day⁻¹)</td>
</tr>
<tr>
<td>8</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (45,000 tonnes.year⁻¹)</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pyrolysis plant (600 odmt.day⁻¹)</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (30,000 tonnes.year⁻¹)</td>
<td>Biomass gasifier + ICE, Power only (0.5 MW)</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pyrolysis plant (600 odmt.day⁻¹)</td>
</tr>
</tbody>
</table>
Table 6.1 (Continued): Alternative supply chain designs obtained in the solution generation stage and ranked in descending order with respect to their NPV

<table>
<thead>
<tr>
<th>Design</th>
<th>Location A</th>
<th>Location B</th>
<th>Location C</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (30,000 tonnes.year(^{-1}))</td>
<td>No technology was recommended</td>
<td>Biomass boiler +steam turbine CHP (1 MW) Pyrolysis plant (600 odmt.day(^{-1}))</td>
</tr>
<tr>
<td>11</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (45,000 tonnes.year(^{-1}))</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pellet plant (15,000 tonnes.year(^{-1}))</td>
<td>Biomass boiler +steam turbine CHP (1 MW) Pyrolysis plant (600 odmt.day(^{-1}))</td>
</tr>
<tr>
<td>12</td>
<td>Biomass boiler + steam turbine CHP (2 MW) Pellet plant (45,000 tonnes.year(^{-1}))</td>
<td>Biomass boiler + steam turbine Power only (3 MW) Pyrolysis plant (200 odmt.day(^{-1}))</td>
<td>Biomass boiler + steam turbine CHP (1 MW) Pyrolysis plant (400 odmt.day(^{-1}))</td>
</tr>
</tbody>
</table>

\(^{a}\)CHP: Combined heat and power  \(^{b}\)ICE: Internal combustion engine
• Demand fulfillment

Table 6-2 demonstrates the average annual and minimum biomass demand fulfillment over the 20-year planning horizon. The conversion facilities that are prescribed for operation in Location C have the lowest demand fulfillment, whereas the rest of the recommended conversion technologies in the other two locations are expected to have satisfying demand fulfillment.

Table 6-2: Average annual and minimum demand fulfillment over the 20-year planning horizon for each potential conversion technology in Design 1 summarized in Table 6-1

<table>
<thead>
<tr>
<th>Candidate location</th>
<th>Prescribed conversion technology</th>
<th>Annual demand fulfillment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Minimum</td>
</tr>
<tr>
<td>A</td>
<td>Biomass boiler + steam turbine CHP a (2 MW)</td>
<td>94%</td>
</tr>
<tr>
<td></td>
<td>Pellet plant (45,000tons/year)</td>
<td>93%</td>
</tr>
<tr>
<td>B</td>
<td>Biomass gasifier + ICE b -Power only (0.5MW)</td>
<td>93%</td>
</tr>
<tr>
<td>C</td>
<td>Biomass boiler + steam turbine CHP (1 MW)</td>
<td>73%</td>
</tr>
<tr>
<td></td>
<td>Pyrolysis plant (600odt/day)</td>
<td>75%</td>
</tr>
</tbody>
</table>

a CHP: Combined heat and power  b ICE: Internal combustion engine

• Net present value

According to the results of the simulation model in the first iteration, the proposed supply design in Chapter 3 (Design 1) has an estimated net present value of $39,302,063 at the operational level; this NPV is considerably lower than that estimated initially by the integrated strategic and optimization mode. Table 6-3 compares the present value of revenue and costs that are obtained from the optimization and simulation models. As seen in this table, the most contributing factor to this difference is revenue. The estimated present value of revenues obtained from the simulation model is around $28,733,793 lower than that obtained from the optimization model.

Table 6-3: Present value (PV) of revenue and costs obtained from simulation and optimization for Design 1 summarized in Table 6-1

<table>
<thead>
<tr>
<th></th>
<th>Value from optimization model</th>
<th>Value from simulation model</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV of revenue</td>
<td>$345,426,937</td>
<td>$316,693,144</td>
</tr>
<tr>
<td>PV of variable costs</td>
<td>$196,373,237</td>
<td>$189,159,047</td>
</tr>
<tr>
<td>PV of investment and fixed costs</td>
<td>$88,232,034</td>
<td>$88,232,034</td>
</tr>
<tr>
<td>Net present value</td>
<td>$60,821,666</td>
<td>$39,302,063</td>
</tr>
</tbody>
</table>
As the results for demand fulfillment indicate, because of the operational level constraints, the amount of biomass that is required to produce the optimal quantity of products prescribed by the optimization model could not be procured. This leads to a lower production quantity of bio-oil product than that prescribed by the optimization model and therefore a lower revenue. According to the results summarized in Table 6-2, the proposed pyrolysis facility seems to have an acceptable demand fulfillment of 88%. However, since the bio-oil product is assumed to have a high selling price, the gap between the revenue obtained from the simulation and optimization models is considerably large.

Figure 6.2 shows the breakdown of the total cost (in present value) obtained from the optimization and simulation models. As this figure depicts, except for the biomass transportation and storage costs, all the cost estimates obtained from the simulation model are lower than those obtained from the optimization model. These differences could be caused by several factors.

Figure 6.2: Breakdown of components of total cost for Design 1 summarized in Table 6-1

One factor is the interaction between the preprocessing and transportation activities. The transportation time in the simulation model is calculated based on the transportation cycle, which includes the travel time for a round trip between the conversion facility and biomass supply sources, and the waiting times for loading and unloading which are uncertain, while these components were not accounted for in the optimization model.

Another reason is that in the simulation model, depending upon the availability of loaders and grinders, when a supplier that is not prescribed by the optimization model does not have enough biomass available or not being harvested yet, the required amount can be supplied from other biomass sources
which might be farther away than what was planned by the optimization model and results in higher transportation costs.

The difference in storage cost between the models is for two reasons. First, contrary to the optimization model, the storage cost in the simulation model includes the fixed ordering costs, which occurs whenever an order for biomass is placed and on time intervals shorter than one month. Second, the inventory holding (or carrying) cost is calculated on a daily basis; whereas in the optimization model the calculation is on a monthly basis, which results in an underestimation of storage costs in the optimization model.

- **Solution improvement**

Then, the solution procedure continues with improving the solution at the tactical level using the iterative hybrid optimization-simulation approach. Table 6-4 illustrates the changes of the NPV in each iteration of the hybrid model. Note that NPV improved over the iterations 1 to 4 and remained almost unchanged after the fifth iteration. Since the gap between the NPV values obtained from iterations 4 and 5 is less than 1%, the stopping criterion is met. Therefore, the solution improvement procedure terminates for the first solution (Design 1), and the overall NPV is set to the net present value obtained from the last iteration of the hybrid model (NPV = $47,869,428). The overall NPV estimated by the hybrid optimization simulation scheme is 21% lower than the \( \text{NPV}_{\text{opt}} = $60,821,666 \) initially estimated from the integrated strategic and tactical model.

<table>
<thead>
<tr>
<th>Iteration</th>
<th>NPV</th>
<th>Percentage of change in NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$39,302,063</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>$43,499,460</td>
<td>10.7%</td>
</tr>
<tr>
<td>3</td>
<td>$46,216,541</td>
<td>6.2%</td>
</tr>
<tr>
<td>4</td>
<td>$47,885,812</td>
<td>3.6%</td>
</tr>
<tr>
<td>5</td>
<td>$47,869,428</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

The improvement in the net present value over the iterations is due to improvement in demand fulfillment of the conversion facilities, especially for the proposed pyrolysis facility in Location C. Figure 6.3 shows the changes in demand fulfillment changed over the iterations.
Figure 6.3: Changes in demand fulfillment of the proposed conversion technologies over the iterations of the hybrid optimization-simulation approach for Design 1 (summarized in Table 6-1)

### 6.3.3 Optimal supply chain design under uncertainty

After $NPV^{sim}$ was found for the base case scenario (Design 1 in Table 6-1), the hybrid approach had to be repeated for other designs listed in Table 6-1 since the $NPV^{opt}$ for the other designs in the solution pool was higher than the overall $NPV$ (from the hybrid model) for the Design 1. Table 6-5 shows how the hybrid approach was proceeded to obtain an overall best solution.

#### Table 6-5: NPV ($) under deterministic and uncertain conditions in the hybrid procedure

<table>
<thead>
<tr>
<th>Design</th>
<th>NPV from optimization model ($)</th>
<th>NPV Hybrid model ($)</th>
<th>Current best solution under uncertainty</th>
<th>NPV from the hybrid model for the current solution &lt; NPV from the optimization model for the next solution?</th>
<th>Should next design be evaluated?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>60,821,666</td>
<td>47,869,428</td>
<td>1</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>2</td>
<td>60,704,838</td>
<td>48,159,793</td>
<td>2</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>3</td>
<td>59,857,713</td>
<td>52,773,086</td>
<td>3</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>4</td>
<td>59,742,647</td>
<td>53,761,212</td>
<td>4</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>5</td>
<td>59,067,002</td>
<td>51,941,251</td>
<td>4</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>6</td>
<td>59,020,676</td>
<td>50,300,825</td>
<td>4</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Table 6-5 (Continued): NPV ($)) under deterministic and uncertain conditions in the hybrid procedure

<table>
<thead>
<tr>
<th>Design</th>
<th>NPV from optimization model ($)</th>
<th>NPV Hybrid model ($)</th>
<th>Current best solution under uncertainty</th>
<th>NPV from the hybrid model for the current solution &lt; NPV from the optimization model for the next solution?</th>
<th>Should next design be evaluated?</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>58,095,298</td>
<td>56,142,904</td>
<td>7</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>9</td>
<td>57,545,813</td>
<td>51,181,854</td>
<td>7</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>10</td>
<td>57,516,440</td>
<td>53,993,499</td>
<td>7</td>
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<tr>
<td>11</td>
<td>57,126,573</td>
<td>53,095,187</td>
<td>7</td>
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<td>No</td>
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<tr>
<td>12</td>
<td>56,029,121</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As illustrated in Table 6-5, the results of the hybrid optimization-simulation approach suggest that Design 7 is the best investment alternative when the dynamics of the supply chain are taken into account. This solution prescribes investing in a pellet facility with an annual operating capacity of 15,000 tonnes per year collocated with a 1 MW CHP facility based on biomass boiler and steam turbine technology in Location A, and a pyrolysis bio-oil production facility with an input capacity of 600 Odmt per day in Location C. The overall NPV for this design (1) is higher than the overall NPV of all the other designs that were simulated (designs 1 to 6, and designs 8 to 11), and higher than the $NPV_{opt}$ for Design 12. The overall NPV for Design 7 is around 17.30% higher than the overall NPV for Design 1, which has the highest net present value under deterministic assumptions, but has the lowest net present value among the designs that were simulated, when variations at the operational level are taken into account.

Compared with the other designs, Design 7 recommends the lowest number of conversion technologies and has the lowest biomass demand, particularly for mountain pine beetle residues. This is because according to the results, the clean woodchips available at the sawmill in Location A would be enough to meet the entire demand of the pellet facility. This eliminates the need for bringing mountain pine beetle residues from forest cut-blocks, which are much dispersed and their transportation is costly. Additionally, the available hog fuel at this location will be sufficient to meet the demand of the 1 MW combined heat and power system in this location; therefore, the need for procuring tops and branches from cut-blocks would be eliminated as well. Furthermore, this design does not prescribe any conversion technology in Location B and no bioenergy technology in Location C. Therefore, there would not be any competition for biomass and logistical resources to meet the biomass demand of the pyrolysis facility.
6.4 Summary and conclusions

In this chapter, a hybrid optimization-simulation scheme was proposed to obtain the design of the supply chain while incorporating the dynamics and variations at the operational level. In this hybrid approach, the optimization and simulation models that were developed independently respectively in Chapter 3 and Chapter 5 were linked together. The integrated strategic and tactical optimization model was used to obtain the design of the supply chain, i.e., capacity and type of conversion facilities to install at each location at the strategic level, and the flow of biomass from supply sources to each potential facility at the tactical level. Then, the simulation model, which incorporated the operational level variations and constraints, as well as interdependencies among various stages of the supply chain, was run to evaluate the annual demand fulfillment of the prescribed design at the operational level. In this hybrid approach, the outputs of the simulation model were used as inputs to adjust the plans from the optimization model.

The developed hybrid model was applied to the case study that was explored in the previous chapters of this dissertation. First of all, the results of the hybrid approach indicated that the net present value of the initial proposed supply chain design in Chapter 3 when variations and constraints at the operational level were taken into account was around 21% lower than that estimated by the optimization model. Additionally, a new solution was found through the hybrid approach which under operational level variations had a 17% higher NPV than the initial solution found through the optimization model. Therefore, the solution obtained from the hybrid approach outperformed the optimal solution from the integrated strategic and tactical model.

Furthermore, the results showed that the variations at operational level had a higher impact on the net present value of the supply chain designs that included larger-sized facilities or larger number of facilities. This is because in both cases, the demand for biomass from cut-blocks was considerably large. Compared with sawmill residues, the availability of residues from forest cut-blocks was characterized by a higher degree of variations. High procurement costs should be spent, e.g., high transportation costs to procure the required amount from longer distances or more storage costs to keep high inventory levels. Additionally, a larger number of conversion facilities led to competition for biomass and logistical resources to meet the biomass demand of the pyrolysis facility.

The key advantage of the proposed hybrid optimization-simulation approach is its capability in providing solutions that are feasible and consistent at strategic, tactical, and operational levels. This was achieved by building the connection between the three planning levels. The feedback exchanged between the operational level and the strategic/tactical level allowed for adjusting the plans taking into account the operational variations in supply chain parameters. However, one limitation of the proposed
hybrid scheme is that, similar to other hybrid optimization-simulation approaches (e.g., in the hybrid model proposed by Ebadian et al. (2014)), it does not guarantee a global optimal solution.
Chapter 7. Conclusions, strengths, limitations, and future research

7.1 Summary and conclusions

Biomass has emerged as an attractive renewable source of energy to shift away from fossil fuels. The high cost of biomass feedstock, lack of reliable supply, and variations are among the key barriers in bioenergy and biofuel development. Therefore, there is a need for comprehensive solution tools to overcome the supply chain planning challenges.

The overall goal of this work was to maximize the net present value of a forest-based biomass supply chain for bioenergy and biofuel production while incorporating the dynamics and uncertainties of the supply chain. This objective was achieved through the progressive construction of a hybrid optimization-simulation model, and the application of model to a case study in British Columbia. In this case study, the potential of producing bioenergy (heat and electricity) and biofuel (pellet and pyrolysis bio-oil) from unused residues of harvesting activities (tops and branches, and non-merchantable logs) and milling activities (sawmill clean chips and hog fuel) was investigated.

In Chapter 2, forest-based biomass supply chain was defined and important considerations in its planning were analyzed. Then, the studies that used different operations research techniques including mathematical programming and simulation modeling for forest-based biomass supply chain planning were reviewed. The review highlighted that the integration of different planning levels was overlooked in the literature. Integrating different planning levels is required to assure that plans from higher levels (e.g. strategic) are attainable at lower planning levels (tactical and operational). This is particularly important in view of seasonality in biomass supply and demand. Medium-term variations in biomass supply and demand create the need for biomass storage and proper inventory management to avoid any interruption in production. Despite its role in costs and efficiency of the supply chain, seasonality in biomass supply and demand were ignored in strategic decision models which dealt with long term investment decision. Additionally, it was discussed that while uncertainties impose a challenge in the economic viability of forest-based biomass supply chains, the literature on bioenergy and biofuel supply chain planning focused on deterministic models; only a few studies incorporated uncertainties in their models. One reason for this is the complexity of conventional techniques, e.g. stochastic programming, to incorporate uncertainty in modeling. These techniques often result in models that require an enormous computational effort for solving difficult problems, such as those that integrate different planning levels. Overall the review revealed that there was a need (1) for supply chain planning models that integrate different planning levels meanwhile capturing the dynamics and uncertainties of the
supply chain, and (2) for solution approaches that can overcome the challenges in incorporating several sources of uncertainty.

Chapter 3 presented the development of an integrated strategic and tactical level optimization model; this model was formulated as a mixed integer linear programming model to maximize the net present value of investment in bioenergy and biofuel projects. In order to address time-varying characteristics of biomass, the model includes a multi-period formulation: annual time steps to address annual variations and monthly time steps to address seasonal variations in biomass supply and demand over the year. A long planning horizon of 20 years was considered to account for variations over the operating life of facilities. Then, the model was modified to a strategic model, in which similar to the common practice in the literature, medium-term variations in biomass supply and demand, consequently, biomass storage and its associated costs were ignored, and the decisions related to biomass and product flows were made on an annual basis. The models were applied to the case study in British Columbia. Using this case study, it was illustrated that when medium-term variations in biomass supply and demand were ignored, the solution from the strategic optimization model was not feasible at the tactical level. First, the biomass demand in selected conversion facilities could not be met in some months. Second, the capacities chosen by the strategic model would not be sufficient to meet the bioenergy demand. Furthermore, the net present value of the strategic model was overestimated. Variations in the monthly availability of biomass necessitate procuring more biomass in some months and storing it or producing and selling less amount of bioproducts; both would impact the net present value negatively. Additionally, the results of the integrated strategic and tactical model revealed that investing in bioenergy and biofuel production can achieve the net present value of $66,821,666.

Although the positive net present value indicated the financial viability of the proposed investment, the conclusions were based on a deterministic model. A part of data was derived from public reports and published literature for similar case studies in other regions. Clearly, there is no guarantee that considered values will be realized. Another part of data was specific to the case study; examples of such data are biomass availability and biomass transportation costs, which were estimated and supplied by FPInnovations. In their estimation process, specific details related to the stand characteristics, utilization standards, biodiversity and soil conservation considerations, technical and handling losses, and the impact of mountain pine beetle on midterm supply were taken into account. However, since biomass availability is very difficult to be exactly measured (Kim, Realff, & Lee, 2011), the estimations are subject to changes and measurement errors. Overall, the data and hence the net present value of the proposed investment could vary in reality.
Depending on the degree of variability in the net present value that a decision maker is willing to withstand and his/her viewpoint towards risk, the proposed investment may or may not be acceptable. Therefore, in Chapter 4, first, a series of sensitivity analyses was performed to examine how the changes in model parameters impact the proposed investment. Then, based on the results of the sensitivity analysis, optimistic and pessimistic scenarios were tailored. In the pessimistic scenario, biomass procurement cost and conventional energy (diesel and hydro) prices were 20% higher, whereas the bioproduct selling prices and biomass availability were 20% lower compared with the base case scenario. Conversely, in the optimistic scenario, biomass procurement cost and conventional energy prices were 20% lower, whereas the bioproduct selling prices and biomass availability were 20% higher compared with the base case scenario. The principles of decision making under uncertainty was employed to propose a suitable supply chain design for different decision making perspectives with respect to risk, i.e., optimistic, pessimistic, and moderately pessimistic.

The results of this chapter suggested that although bio-oil and pellet products contributed largely to the profit, investing in biofuel and bioenergy projects together is risky as it increases the demand for biomass, especially forest residues that should be procured over long distances. Considering the dispersed availability of harvesting residues, the dependency on harvesting residues increases the risk of the investment not only to variations in biomass availability and procurement cost but also to the variations in the bioproduct selling prices, which should be high enough to justify biomass procurement cost and low enough to compete with conventional alternatives. This type of investment might be appealing if the decision maker is optimistic or moderately pessimistic. However, for a new industry like bioenergy and biofuel production, investors tend to be pessimistic and therefore risk-averse. For a pessimistic investor, the results recommended investing in small scale bioenergy technologies within existing traditional forest industry, e.g., sawmills. With small scale bioenergy production, it would be possible to rely solely on in-house generated residues, which are available free of charge. Since this type of residue does not need procurement, the risk of the investment with respect to variations in biomass procurement cost and biomass availability is lower than that in the base case study.

Chapter 5 presented the development of a discrete event simulation model to evaluate the performance of different inventory management systems for managing the proposed supply chain design in Chapter 3, taking into account the impact of supply chain complexities. Two continuous inventory systems: 1) order-up-to-level, and 2) fixed order quantity were compared in terms of their total logistics cost, total CO₂ eq emission, and annual demand fulfillment. Uncertainties in biomass availability, bulk density, and machine productivities were taken into account. Additionally, other complexities such machine interaction and time dependency of different stages of the supply chain were included in the model.
The results indicated that the selection of the inventory management system impacted the annual demand fulfillment slightly, but affected considerably the total logistics cost and total CO2 eq emission of the supply chain. For the given case study, the fixed order quantity system showed up to 2% higher demand fulfillment. This slightly better demand fulfillment was achieved by storing more biomass. Storing larger quantities of biomass increased the required operating hours for biomass preprocessing and transportation by up to 50%, and consequently increased the total cost by up to 34% and total CO2 eq. emission by up to 14%. The results of scenario analysis emphasized that a slight improvement in demand fulfillment for each individual inventory system would require considerable expenditure on operating costs and would result in increased emission. This indicated that the selection of a proper inventory management system offers the possibility to reduce the logistics costs and emissions, which is a determining factor in enhancing the competitiveness of biomass as a replacement for fossil fuels.

In Chapter 6, an iterative procedure was developed to integrate the optimization and simulation models. In this iterative approach, alternative supply chain designs with positive NPV were generated. For each alternative, the strategic and tactical plans from the integrated strategic and tactical optimization model were used as inputs to the simulation model. In the simulation model, the demand fulfillment and the net present value of the supply chain were evaluated considering the dynamics, stochastic nature, and operational level constraints (e.g., availability and the productivity of the machinery and equipment). In return, the simulation model provided the optimization model with the information about the demand fulfillment, based on which, the tactical procurement plans were adjusted in the optimization model. The iterative procedure was repeated until no considerable change was observed in the demand fulfillment and supply chain design under uncertainty. This process was repeated for all the identified supply chain designs until one that had the best net present value under uncertainty was found. The solution of this model (i.e., technology type, size, and location of facilities, the selection of biomass supply sources and the amount of biomass to procure) differed from the solution when operational level complexities were ignored. The results of the hybrid optimization simulation model recommended investing in a pellet facility with annual output capacity of 15,000 tonnes per year together with a 1 MW combined heat and power facility in Location A and a 600 Odmt per day biomass pyrolysis facility in Location C. The prescribed design by the hybrid model included fewer and smaller conversion facilities compared with the initial supply chain design that was proposed by the integrated strategic and tactical optimization model in Chapter 3, but more and larger facilities compared with the supply chain design suggested in Chapter 4 as a suitable design for a pessimist decision maker. One common conclusion that can be made analyzing the results of Chapter 4 and Chapter 6 is that biofuel production and high reliance on biomass from forest cut-blocks, which were much diffused over a large area, increased the sensitivity of the net present value to the variations across the supply chain.
Based on the results of the hybrid model, a net present value of $56,142,904 (equivalent to equal annual profits of $6,594,524) was achieved for this investment when the impact of operational level complexities was accounted for. This net present value was around 17.30% higher than the net present value of the initial proposed supply chain design when operational level variations and complexities were ignored. This signifies the importance of developing decision support tools that can capture the impacts of biomass supply chain dynamics and stochastic nature on its design and management.

The overall findings of this dissertation indicated the profitability of investing in bioenergy and biofuel production. However, this conclusion should be interpreted with caution since not all the conversion technologies (e.g., pyrolysis) that are considered herein are commercialized, the demand for the products are not fully developed and understood yet. Due to lack of historical data, the estimated profit might not be accurate. Moreover, as the results of the sensitivity analyses in Chapter 4 revealed, the variations in model parameters may severely impact the profitability of the proposed investment. Therefore, the results and conclusions of this study are not intended to recommend investing in the technologies that were suggested by the developed models in the case study region.

7.2 Strengths

From the modeling perspective, the main strength of the proposed model in this research is that it integrates simultaneously strategic and tactical level planning while accounting for the dynamics, stochastic nature, and operational level constraints of the supply chain.

The proposed hybrid model in this work allowed for incorporating the complexities of the supply chain without experiencing any computational difficulty. This was important since even without operational level complexities, the optimization model presented a supply chain model with a large number of variables and constraints (4,734,483 decision variables (2400 binary) and 2,006,883 continuous variables) and required handling a large amount of data. Therefore, conventional techniques for addressing uncertainties, if employed, would have required enormous computational effort to obtain the solution.

The hybrid optimization-simulation model proposed in this research is the first application in forest-based biomass supply chains that integrates mathematical programming and discrete event simulation modeling to tackle the complexities of the supply chain. However, Ebadian et al. (2014) applied hybrid optimization-simulation for the planning of an agricultural-based biomass supply chain for ethanol production. Since the operations in agricultural supply chains are different from those in forest-based biomass supply chains, their discrete event simulation was different from the simulation model in this study. Additionally, Ebadian et al. (2014) used their hybrid approach to integrate the tactical and
operational levels, therefore, in their model, the strategic design of the supply chain, i.e., the location and capacity of the ethanol plant, was given. Hence, their optimization model was different, too. Similar to the current study, the linkage between the simulation and optimization models in Ebadian et al. (2014) was based on biomass shortage. However, the iteration between the optimization and simulation models in (Ebadian et al., 2014) was terminated when the same plans were obtained from two consecutive runs of the optimization model and therefore they developed a different stopping criterion.

Hybrid optimization-simulation modeling was used in the forest products industry in a few studies. The majority of the existing hybrid optimization-simulation approached used a simulation model to evaluate the solution of an optimization model or to estimate the input parameters for an optimization model. In some cases, the feedback from one model to another might be important in the choice of the final solution, particularly when uncertainties are of importance. In this case, the optimal solution of a deterministic optimization might be infeasible when simulated in an uncertain environment. Unlike the hybrid optimization simulation models that were developed to handle complexities of problem-solving in forest product supply chain planning, the hybrid model in this dissertation was developed to find the solutions that are feasible and consistent at strategic, tactical, and operational levels. This was achieved through the building of a linkage between the three planning levels which allowed adjustment of the plans based on the variations in supply chain parameters through exchanging the feedback between the operational level and the strategic/tactical levels.

The optimization and simulation components of the hybrid approach in this dissertation are developed independently and can be applied to similar case studies individually or together as in the hybrid approach. Depending on biomass and product types modifications might be needed to be made in the simulation and/or optimization models. However, the general structure of the hybrid model is applicable to other cases without limitations.

In developing the integrated strategic and tactical optimization model developed in Chapter 3, A more complex supply chain was taken into account, compared with the models in similar studies (Ekşioğlu et al., 2009; Memişoğlu & Üster, 2015); the supply chain in this work included different bioenergy and biofuel products and a large number of candidate conversion technologies in various capacity ranges. A longer planning horizon was taken into account to address variations in biomass supply from year to year over the entire operating life of conversion facilities. Optimizing the design of a forest-based biomass supply chain based on the decision maker’s perspective with respect to risk was another topic in this dissertation that was not received attention in literature related to forest-based biomass supply chain planning previously.
The feasibility of a forest-based supply chain was evaluated in some previous simulation studies considering complexities of the supply chain, such as seasonality in biomass supply and demand, interdependencies, and uncertainties. Despite the key role of inventory management systems in improving the demand fulfillment and securing a continuous year-round production at a minimized cost, it was not addressed in any of the previous studies. Evaluating the impact of alternative inventory management system on demand fulfillment, total cost and total CO2 eq emissions of the supply chain constitutes another strong point of the current dissertation.

Eventually, the case study herein included a large amount of data and information related to the technical and economic aspects of bioenergy and biofuel production. These data could be useful in other relevant studies.

7.3 Limitations

One limitation of this study is that its emphasis was on the profitability of making investments in bioenergy and biofuel projects. Biomass is considered as a sustainable alternative to fossil fuels, therefore, other than profitability, other pillars of sustainability, which are environmental and social impacts (Evans, Strezov, & Evans, 2009), deserve further consideration in order to prevent introducing adverse impacts on environment and society.

The application of the optimization and simulation models required large amounts of data, which were collected from various sources. The validity of the results was assessed but not all the collected data were first-hand data. The candidate technologies and their operating capacities were adopted from feasibility studies performed by FPInnovations (Marinescu, 2012, 2013), which were initiated based on the existing interest of stakeholders and also considering the energy demand profile of the considered communities. The production capacity for pellet and bio-oil conversion technologies were taken from (Cambero, Sowlati, et al., 2015), in which the sizes for pellet and pyrolysis technologies and the demand for wood pellets and bio-oil were estimated considering the total economically available biomass. Moreover, due to lack of data, availability of residues from sawmills and the demand for biofuel products were assumed to be fixed over the year. Therefore, a detailed supply and demand analysis can enhance the applicability of the case study results.

In this dissertation, several sources of uncertainty, such as those in biomass availability, bulk density, and transportation times, were incorporated in the model, while being highly variable in reality, biomass quality attributes (e.g., moisture content and ash content) were assumed to be fixed. This may impact considerably the results since the variations in biomass quality can lead to considerable financial losses. As the sensitivity analyses in Chapter 4 indicated, pellet and bio-oil products were the most profitable
products of the proposed supply chain design. Pellet production equipment is designed to work with biomass with specific ash content and low moisture contents. Additionally, the amount of bio-oil yield and its quality (e.g. acidity and heat value) depend on biomass moisture content and ash content. Upon availability of data, the probability distribution functions of the quality attributes of biomass can be estimated and incorporated into the simulation model without any further change to the model.

Another limitation is that the duration of transporting harvesters and grinders between cut-blocks were calculated based on Euclidean distance between the center points of cut-blocks since the geographical locations for residues piles and the forest service road were not available. However, Euclidian distance tends to underestimate the actual transportation distances and travel times (Shahid, Bertazzon, Knudtson, & Ghali, 2009). As the results showed the transportation cost had the largest contribution to the total logistics cost. Therefore, it is important to use methods that yield better estimations of transportation distances.

In this study, biomass conversion to bioenergy and biofuel products were modeled as black boxes with linear material and energy balance functions. Process simulations can be employed to represent complex non-linear processes, which are a more realistic representation of conversion processes at the facility level.

The hybrid optimization simulation scheme that was proposed in Chapter 6 is an iterative model. In this scheme, a stopping criterion was used to terminate the iterative process. However, the model might perform differently under various stopping criteria. Therefore, there is potential in investigating the effect of different stopping criteria and recommending a suitable criterion.

**7.4 Future research**

A potential direction for future research is to extend the integrated strategic and tactical optimization model to a multi-objective model to address the environmental and social gains of bioenergy and biofuel production. This requires (1) performing life cycle assessment for determining the environmental impacts associated with all the stages of bioenergy and biofuel production, (2) identifying an indicator for quantifying the social gains, and (3) developing environmental and social objective functions.

Considering that transportation sector is the second largest contributor to the total greenhouse gas emission in Canada (Environment and Climate Change Canada, 2017), the model can be extended to include potential technologies and capacities for upgrading pyrolysis bio-oil to transportation fuels, such as diesel, jet fuel, and gasoline. In this regard, the model might be further extended to include centralized and decentralized conversion processes. In the centralized process, bio-oil production and
upgrading take place at the same location, whereas, in the decentralized process, biomass is first processed into bio-oil. The bio-oil is then transported to other locations where it is upgraded to final products.

Future studies should account for uncertainty in other parameters of the model, e.g., in biomass quality, equipment failure and repair times, product demand and prices. To achieve this, the probability distribution functions for uncertain parameters should be estimated and incorporated into the simulation model.

In order to get more realistic estimates for performance measures, the simulation model in this work can be integrated with a geographic information system (GIS) to define actual distances and travel times. However, the possibility of this integration depends on the availability of the geographical location of piles of residues and the forest service road network over the planning horizon.

Finally, the proposed hybrid scheme should be applied to other case studies to evaluate whether the iterative procedure terminates within a reasonable time or not. Moreover, the hybrid scheme should be tested with other stopping criteria to find out how the stopping criterion might change the final solution.
References


