Integrated Forest Biorefinery Network Design Under Uncertainty

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Abstract

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The Canadian Pulp and Pulp (P&P) industry has been recently confronted by shrinking markets and tighter profit margins. Transforming P&P mills into Integrated Forest Biorefineries (IFBR) is a prominent solution to save the struggling industry and allow diversification towards the promising bioproducts markets. The implementation of such a strategy is a complex process that faces many sources of uncertainty. Therefore, the industry is in need for a planning tool that facilitates the IFBR network design by taking the uncertain market conditions into consideration.

First, we propose a mixed integer programming model to optimize the investment plan in addition to other tactical decisions over a long-term planning horizon. We test the model using a realistic case study for Canadian P&P companies, where we perform a set of sensitivity analysis tests in terms of bioproduct demand and energy prices. Our results showcase the potential of the IFBR to help the P&P industry and highlight the substantial impact of the bioproduct demand on its profitability.

Second, we develop a Multi-stage Stochastic Programming model which explicitly incorporates the demand uncertainty. We also develop a simulation platform to validate the model and compare its performance with alternative decision models. We assess the value of incorporating demand uncertainty in the planning process and we also elaborate on the value of flexibility in terms of adjusting the investment plan in response to changes in market trends. Our results demonstrate the significant value of explicitly incorporating the uncertainty in IFBR network design as well as flexibility in the investment plan.

Preface

This thesis has been prepared in "Manuscript-based" format under the co-supervision of Dr. Masoumeh Kazemi Zanjani from the department of Mechanical, Industrial and Aerospace Engineering, Concordia University; and Dr. Mustapha Nourelfath from the department of Mechanical Engineering, Laval University.

All the articles presented in this thesis were co-authored and reviewed prior to submission for publication by Dr. Masoumeh Kazemi Zanjani and Dr. Mustapha Nourelfath.

The author of this thesis acted as the principal researcher and performed the mathematical models development, programming of the solution algorithms, analysis and validation of the results, along with writing the first drafts of the articles.

The first article entitled "Integrated Forest Biorefinery Network Design", co-authored by Dr. Masoumeh Kazemi Zanjani and Dr. Mustapha Nourelfath was published in the proceedings of the International Conference on Information Systems, Logistics and Supply Chain, July 8-11, 2018, Lyon, France.

The second article entitled "Integrated Forest Biorefinery Network Design Under Demand Uncertainty", co-authored by Dr. Masoumeh Kazemi Zanjani and Dr. Mustapha Nourelfath was submitted to *International Journal of Production Research* in October 2019.

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My deep love and appreciation goes to my parents for their support, kindness and patience in every stage of my life. They always tried to provide the best opportunities for my education. I would also like to thank my brothers and sister for their love and support. A special thanks to my older brother Ahmed for his endless support and accompanying me on this journey. Finally, I would like to thank all my friends for their encouragement and support.

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Chapter 1

Introduction

1.1 Overview and problem statement

The Canadian Forest sector is a major contributor to the Canadian national wealth by providing a variety of economic, social and environmental benefits. Economically, the Canadian forests sector directly contributed $24.6 billion to Canada's nominal gross domestic product (GDP) in 2017, which represents around 1.6% of Canada's GDP [1]. Socially, the different industries operating in the Canadian forests directly provide more than 200 thousand jobs and these jobs immensely contribute to the development of rural and remote communities [2]. Environmentally, the Canadian forest, which covers an area of 347 million hectares, plays an important role in balancing the Earth's CO2 supply and exchange in addition to being home to an immense diversity of species [3], [4]. In order to ensure the sustainability and well-being of this paramount resource, Canada was one of the early adopter of sustainability concepts in forestry, starting with the national forest strategy of the Canadian Council of Forest Ministers (CCFM) for the year 1992 [5].

Sustainability concepts in forestry include forest management which refers to the application of biological, physical, quantitative, managerial, economic, social, and policy principles to ensure the regeneration, utilization and conservation of forests [6]. One of the key principles of forest management is the sustainable utilization of forest resources by ensuring the efficiency of forestry operations and industry. This encouraged researchers to contribute to the sustainable utilization of forest operations especially in terms of applying Operations Research (OR) methods and techniques

[26]-[36]. Various decision support, planning and design algorithms and models developed based on OR methodologies have been applied in different forest sectors so as to maximize the value from this natural resource and reduce waste. The aforementioned approaches also benefit companies operating in the forestry sectors by improving their operations and, in turn, their profitability.

The Pulp and Paper (P&P) industry is one of the main industries operating in the Canadian forests. It contributes \$8.9 billion to Canada's GDP which represents 36% of the total contribution of all forest industries [1]. This industry operates P&P mills which rely on using wood as raw material to produce pulp, paper, paperboard and sometimes other cellulose-based products. The processes employed in these mills are energy-intensive and they produce byproducts which, traditionally, are not utilized and are rather considered as waste [7][8]. Moreover, the majority of P&P mills in Canada still employ old processes and techniques, and the industry is considered unmodernized and in need of development and improvements in terms of operational efficiency [8].

Over the last decade, Canadian forest sector and P&P companies in particular have been confronted by a series of challenges which left them struggling to maintain competitiveness in an increasingly competitive business environment. Saturated markets due to excess global supply along with low-cost competition from emerging economies lead to tighter-profit margins for the entire forest industry. Canadian P&P companies in particular, have been severely affected by these challenges because of the structural decline in the demand of conventional P&P products due to the digitalization of paper-based media. Moreover, political issues in recent years and resulting trade disputes have negatively affected the industry and highlighted the vulnerability of this trade-exposed, commodity-focused sector [9]. The effects of this increasingly competitive economic environment are amplified by the inefficient cost structure of P&P mills and higher energy costs [10].

A growing number of industry experts and researchers have been highlighting the need for P&P companies to transform their business model in order to survive and regain profitability [8], [10]-[11]. The strategies outlined in these works focus on changing the main aspects of the P&P business model; involving products, customers and markets in order to deal with the aforementioned challenges. The solutions proposed in these works fall under two main avenues: i) modernizing and optimizing the existing manufacturing processes and operations; and ii) integrating new high-value-added products in their products portfolio. The latter avenue of solutions has been identified by multiple works in the literature as the more promising option as it enables P&P companies to access new markets and diversify away from the diminishing pulp and paper markets. This strategy change can be achieved by transforming conventional P&P mills into Integrated Forest Biorefineries (IFBR) that rely on the conversion of biomass resources available to forest management companies into a range of biochemicals, biofuels, and bioenergy.

1.2 Integrated Forest Biorefinery (IFBR)

A Biorefinery is a facility that utilizes biochemical and thermochemical processes and technologies in order to convert different types of biomass into biofuels, biochemicals and bioenergy. The biorefinery is identified as part of the solution to climate change and the world dependence on fossil fuels. The products provided by the biorefinery are seen as a substitute for petroleum-based fuels and energy, and the technologies and production processes used at the biorefinery have lower environmental impact than their petroleum counterparts [12].

The Integrated Forest Biorefinery (IFBR) is a biorefinery that is based in the forest industry, where it can utilize the biomass accessible to the industry and the byproducts of some activities in the forest industry in order to operate and produce a variety of bioproducts. Moreover, the bioenergy generated at the IFBR in the form of heat and/or electricity can be used to fulfil the energy demands of some operations in the forest industry. In the context of the P&P sector, the IFBR could benefit from the available infrastructure at the P&P mills for technological implementation of the IFBR processes; while the P&P mills, which are heavy energy consumers, can rely on the IFBR for its energy requirements. Moreover, some byproducts from P&P operation can be used as biomass for the IFBR.

The IFBR value creation chain incorporates biomass suppliers (procurement) at the upper echelon, P&P mills and biorefinery in the middle echelon (production), and the different demand markets at the lower echelon.

The biomass feedstock which is the raw material used at IFBR consists of multiple types that can be procured from a variety of sources. There are two main categories of biomass for biorefinery uses. The first category includes corn grain, corn starch, sugar cane, soy bean, etc. Biomass from this category is believed to have an adverse effect on food production and prices. The second category of biomass is cellulosic-based biomass which does not have an impact on the food supply as it is non-starch, non-edible and non-food feedstocks. The latter category includes forest residues such as tree bark and wood waste; and industrial residues from forest-based industries such as wood chip and saw dust. Other types of biomass includes energy crops which are specifically grown for energy uses, and aquatic biomass such as algae and cyanobacteria [12].

In the middle echelon, the IFBR processes and technologies are utilized to convert the biomass feedstock to bioproducts. There is a variety of different technologies and processes available to biorefineries including palletization, pyrolysis, fermentation, gasification, cogeneration, hydrolysis and digestion. However, the maturity degree of these technologies varies between commercial scale status and pilot or demonstration projects.

The IFBR is capable of producing a wide range of products depending on the technologies and processes implemented. The main type of products produced at the biorefinery are biofuels such as bioethanol, synthetic natural gas, biodiesel and pellets. The reason for the popularity of biofuels is that they offer a greener substitute for petroleum-based fuels which falls in line with the goals of many countries to decrease their dependency on petroleum products. Additionally, biorefineries produce organic chemicals (biochemicals) such as biopolymers and bio-pesticides; and non-conventional biomaterials and composites [13].

There are numerous sources of uncertainty that affect the IFBR supply chain and impact the success of the IFBR transformation for P&P companies. A review of uncertainty concepts in biofuel supply chains is presented in [14]. The review mentions 4 main categories of uncertainties which are biomass supply uncertainty, production and operations uncertainties, transportation and logistics uncertainties, and demand and price uncertainties.

The biomass supply is cyclical, unstable and unstandardized which leads to uncertainty in terms of raw material yield, type and quality. The uncertainty in production and operations results from the fact that biorefinery technologies are not fully mature and their conversion rates or yields are not stable yet. However, the technology used in biorefineries is expected to improve in the future as a result of research and development efforts [15][16]. The third type of uncertainty concerns logistics, which encompasses transportations costs, delays and perturbations to the transportation network.

The last category of uncertainty mentioned in this review is demand and prices uncertainty. The demand markets for bioproducts are still relatively new and volatile, which leads to uncertainty in demand quantities and prices of bioproducts. Many researchers identify the demand uncertainty in the IFBR network design as the most impactful source of uncertainty as it has substantial effect on long term investment in IFBR facilities (see e.g. [17]). Other types of uncertainties affecting the IFBR supply chain include governmental incentives and regulatory policies which are required to help the bioproducts industry compete with the petroleum industry.

Although the IFBR transformation is one of the most promising strategies to save the struggling P&P industry, the implementation of such a strategy is a very complex project as it involves product portfolio decisions, investment planning, technology selection, production planning, and market selection [15]. As a result of the complexity of the IFBR transformation solution and the numerous uncertainties that affect the success of this solution; the Canadian P&P companies are in need for a practical and holistic planning and decision-support tool, which takes into consideration the uncertainties affecting the IFBR. In other words, the proposed investment plan in terms of the choice of technology, in addition to other tactical decisions must be robust and flexible as the uncertain factors (such as market conditions) evolve over time. Nevertheless, to the best of our knowledge, less effort has been done in the literature in explicitly incorporating uncertainty in the IFBR network design.

1.3 Thesis objectives and organization

In this thesis, with the goal of facilitating the IFBR transformation strategy and protecting the IFBR investment plan against uncertainty, we aim to design a comprehensive planning and network design tool that will aid in developing a robust investment plan for the implementation of IFBR transformation strategy in the context of P&P companies in Canada.

The aforementioned goal can be broken down into the following objectives:

(1) To formulate the problem of IFBR network design over a long-term planning horizon as a deterministic optimization model, based on existing models in the literature, that is compatible with realistic IFBR configuration for P&P companies in the province of Quebec.

(2) To develop a realistic case study that reflects the reality and trends of the P&P industry in

Canada based on reports and reviews regarding the industry in the region. The data collected and consolidated to compose this case study can be found in Appendix A.

(3) To identify the sensitivity of the IFBR investment plan to changes in the demand and changes in energy prices.

(4) To model the uncertain bioproduct demand over a long-term investment horizon such that the dynamic behavior of demand over time is taken into consideration.

(5) To explicitly incorporate the uncertainty in the IFBR planning process and to formulate the IFBR network design problem as a Multi-stage Stochastic Programming (MSP) model.

(6) To develop a simulation platform that will help test the performance of the developed MSP model under realistic circumstances.

(7) To verify the value of flexibility in IFBR planning by comparing different model plans using the developed simulation platform.

(8) To analyze the results in the aforementioned objectives to draw useful managerial insights for P&P companies.

This thesis has five chapters organized as follows. Chapter 2 presents the fundamental principles of Stochastic Programming and the techniques adopted for use in this thesis. Chapter 3 addresses the formulation of the IFBR network design problem as a deterministic optimization model and the identification of solution sensitivity to changes in demand and energy prices. Chapter 4 concerns the incorporation of uncertainty in IFBR network design which includes the development of the MSP model, the development of the simulation platform and the identification of the value of flexibility in IFBR planning. Finally, Section 5 summarizes concluding remarks in addition to providing several avenues for future research.

Chapter 2

Stochastic Programming

One of the main assumptions of linear programming (LP) models is that model parameters are known with certainty or deterministic. This is not a realistic hypothesis in most cases; even the most sophisticated forecasting approaches are not able to precisely predict the outcome of uncertain parameters in decision models, such as demand, price, etc. Stochastic programming [18] [19] [20] [21] was proposed in order to deal with mathematical programming problems that involve random parameters. In what follows, we present the general characteristics of mathematical models with random parameters.

Given that we are addressing a multi-period problem, we begin by abstracting the statement of a multi-period LP model with random parameters:

$$
\begin{aligned}
&\textit{Minimize} \quad c_1x_1 + c_2x_2 + \ldots + c_Tx_T, \\
&\textit{Subject to} \\
&\qquad A_{11}x_1 \qquad\qquad\qquad\qquad = b_1, \\
&\qquad A_{21}(\omega)x_1 + A_{22}(\omega)x_2 \qquad = b_2(\omega), \\
&\qquad \vdots \\
&\qquad A_{T1}(\omega)x_1 + \ldots + A_{TT}(\omega)x_T = b_T(\omega), \\
&\qquad x_1 \geq 0, x_2 \geq 0, \ldots, x_T \geq 0.
\end{aligned} \tag{1}
$$

where ω denotes a random vector varying over a set $\Omega \subset \mathrm{R}^k$. We assume that a family F of "events", i.e., subset of Ω corresponding to the random parameters in model (1) with the probability distribution P are given. Furthermore, we assume that the probability distribution P is independent of x. However, the above problem is not well defined and revision of the modeling process is necessary to find the deterministic equivalent. Depending on how we revise the model; we could have multiple types of stochastic programming models.

We confine our attention to the case where the random parameters are modeled as discrete scenarios. Given that our problem is multi-period, the stochastic programming (SP) models under consideration are two-stage stochastic programming and multi-stage stochastic programming (MSP). In this section, we only elaborate on multi-stage stochastic programming. In the following, we first discuss the approaches to model uncertainty in random parameters; then we provide the general concept as well as mathematical formulation of multi-stage stochastic programs with recourse.

2.1 Modeling the random parameters

In multi-period optimization with randomness, the random data can be treated either as a random variable with a stationary probability distribution, or as a non-stationary and dynamic data process. Both approaches rely on modeling the random parameters into a set of discrete scenarios. The scenarios can be derived from discretizing probability distributions or they can be developed based on experts' opinions.

In the first approach, the random data is assumed to have a stationary behavior and thus it is modeled as random variables with stationary probability distributions. This corresponds to a number of scenarios with known probabilities; where the scenarios do not depend on time periods and are defined for the entire planning horizon.

The second approach models the random data as a dynamic process which is represented by a scenario tree. In a scenario tree, the planning horizon is segmented into stages representing the time when new information on the random data is available. The scenario tree consists of nodes where each node represent an outcome of the random event at a certain stage. The root node of the tree represents the current state of the world and the branches (arcs) denote the scenarios for the next stage. Each arc has a given probability and the probability of each node in the scenario tree is the product of probabilities of the arcs from the root node to that node. The sum of probabilities of nodes at each stage is equal to 1. Scenarios are defined as a path from the root node to a leaf node. 2.1 illustrates and compares the stationary and dynamic behavior of random parameters over time.

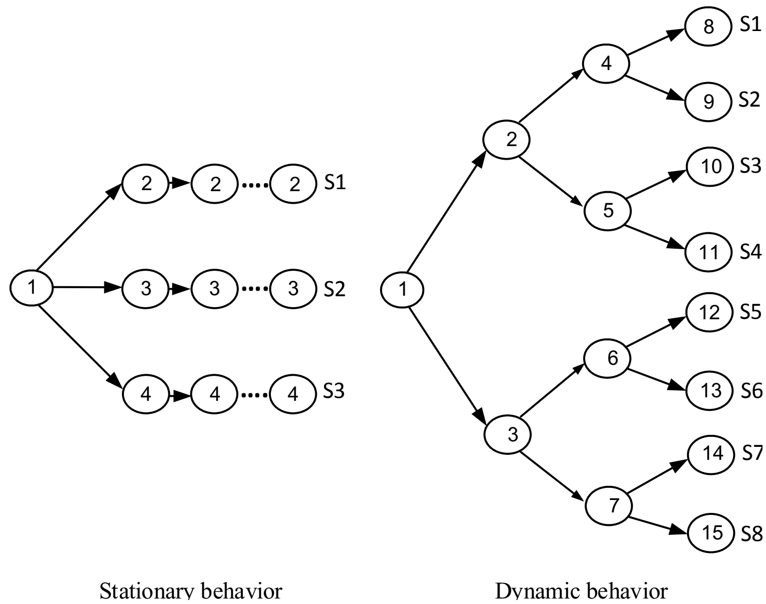

Figure 2.1: Stationary vs. dynamic random parameter behavior over time

After modeling the random parameters as a scenario tree, the uncertain optimization model is transformed into a deterministic equivalent model. In the following, we elaborate on multi-stage stochastic programming.

2.2 Multi-stage stochastic programming (MSP)

In MSP, the decision model is designed to allow the user to adopt a decision policy that can react to events as they unfold. The form of the decisions depends on assumptions concerning the information that is available to the decision maker, when (in time) is it available and what adjustments (recourses) are available to the decision maker. The uncertainty is represented through a scenario tree and an objective function is chosen to represent the risk associated with the sequence of decisions to be made; and the whole problem is then solved as a linear program. The MSP formulation is explained in the following.

2.2.1 MSP formulation

Consider model (1) and assume the random vector ω is represented by a scenario tree. The deterministic equivalent of a multi-stage stochastic model can be formulated as follows:

Since a scenario represents a path from the root node to each leaf node in the scenario tree; let a scenario s corresponds to a single setting of all data in model (1),

$s = \{A_{tt'}, b_t : t = 1, ..., T, t' = 1, ..., T\}$,

and a decision x corresponds to a single setting of all the decision variables

$x : (x_1, ..., x_T) \in \mathrm{R}^{n_1} \times ... \times \mathrm{R}^{n_T}$.

Solving the deterministic LP model (1) for a given scenario s of the data is equivalent to solving the following problem for a certain function:

min $\quad f(x, s) \qquad$ over all x

where

$$f(x,s) = \begin{cases} \sum_{t=1}^{T} c_t x_t, & \text{if } x \text{ satisfies all constraints in (1),} \\ +\infty & \text{otherwise.} \end{cases}$$

The function $f(., s)$ is called the essential objective function for the LP model (1). By setting its value to plus infinity for all points that violate the constraints, we ensure that minimizers of $f(., s)$ will be feasible for the LP model (1).

We next develop the stochastic model. Let us suppose that we are given a set S of scenarios on a scenario tree. We first, set a policy that makes different decisions under different scenarios. Mathematically, a policy X that assigns to each scenario $s \in S$ is a vector

$X_s = (X_{1s}, X_{2s}, ..., X_{Ts})$,

where $X_t(s)$ denotes the decision to be made at stage t if encountered by scenario s. Decisions made for individual scenarios do not protect against the possibility that other scenarios may occur. Moreover, the decision process must conform to the flow of available information, meaning the decisions must be non-anticipative (or implementable). A decision is said to be implementable if for every pair of scenarios s and s' that are indistinguishable up to stage t then

$(X_1(s), ..., X_T(s)) = (X_1(s'), ..., X_T(s'))$.

As the examples of indistinguishable scenarios, refer to scenarios 1, 2, 3, and 4 in node 2 at stage 2 of the scenario tree in 2.1. Implementability guaranties that policies do not depend on information that is not yet available. The multi-stage stochastic programming can be formulated as:

min $\left\{\sum_{s\in S} p_s f(X(s), s) | X \text{ is an implementable policy}\right\}$,

where p_s denotes the probability of scenario s. There are two approaches to impose the non-anticipativity constraints (NAC) in the multi-stage stochastic programs which lead to split variable formulation and compact formulation.

Split variable formulation

In split variable formulation, the decisions are defined for every stage and every scenario in the scenario tree, and the NAC are explicitly enforced based on the shape of the scenario tree. Model (1) can be represented by the split variable formulation as follows:

$$\begin{aligned}
&\textit{Minimize} \quad \sum_{s\in S} p_s[c_1x_1(s) + c_2x_2(s) + ... + c_Tx_T(s)] \\
&\textit{Subject to} \\
&\qquad A_{11}x_1 = b_1, \\
&\qquad A_{21}(s)x_1(s) + A_{22}(s)x_2(s) = b_2(s), \quad s \in S, \\
&\qquad \vdots \\
&\qquad A_{T1}(s)x_1(s) + ... + A_{TT}(s)x_T(s) = b_T(s), \quad s \in S, \\
&\qquad x_1(s) \geq 0, x_2(s) \geq 0, ..., x_T(s) \geq 0, \quad s \in S, \\
&\text{non-anticipativity constraints} \\
&\qquad x_2(s) = x_2(s'), \quad s, s' \in \{s\}_2, \\
&\qquad \vdots \\
&\qquad x_T(s) = x_T(s'), \quad s, s' \in \{s\}_T,
\end{aligned} \tag{2}$$

where $\{s\}_t$ denotes the set of all indistinguishable scenarios at stage t of the scenario tree.

Compact formulation

In the compact formulation, the decision variables are associated with the nodes in the scenario tree and thus the NAC is imposed in an implicit way.

To represent model (1) by the compact formulation, consider a scenario tree with $t = 1, ..., T$ stages, where the nodes for stage t are indexed by k_t. There are $\mathrm{K}_t - \mathrm{K}_{t-1}$ nodes indexed by $k_t = \mathrm{K}_{t-1} + 1.....\mathrm{K}_t$ for stage t ($\mathrm{K}_1 = 1$); particularly, the $\mathrm{K}_T - \mathrm{K}_{T-1}$ nodes indexed by k_T correspond to the leave nodes which also represent the scenario. All the decision variable in MSP compact formulation are associated with the nodes in the scenario tree where each node has a probability of p_{k_t}. The objective function now represents the expected cost of the decision policy. Model (3) represents the transformed model (1) into the deterministic equivalent of multi-stage stochastic model, based on a given scenario tree.

$$
\begin{aligned}
&\textit{Minimize} \quad c_1^T X_1 + \sum_{k_2=2}^{K_2} p_{k_2} c_2^T X_{k_2} + \sum_{k_3=K_2+1}^{K_3} p_{k_3} c_3^T X_{k_3} + ... + \sum_{k_T=K_{T-1}+1}^{K_T} p_{k_T} c_T^T X_{k_T} \\
&\textit{Subject to} \\
&\qquad A_{11} X_1 = b_1, \\
&\qquad A_{k_2 1} X_1 + A_{k_2 2} X_{k_2} = b_{k_2}, \quad k_2 = 2, ..., K_2, \\
&\qquad\qquad A_{k_3 2} X_{a(k_3)} + A_{k_3 3} X_{k_3} = b_{k_3}, \quad k_3 = K_2 + 1, ..., K_3, \\
&\qquad\qquad\quad \ddots \qquad\qquad \ddots \\
&\qquad\qquad\quad A_{k_T, T-1} X_{a(k_T)} + A_{k_T, T} X_{k_T} = b_{k_T}, \quad k_T = K_{T-1} + 1, ..., K_T, \\
&\qquad X_{k_t} \geq 0, \qquad k_t = k_{t-1} + 1, ..., K_t, \quad t = 1, ...T.
\end{aligned} \tag{3}
$$

It should be noted that in multi-stage stochastic model (3), $a(k_t)$ denotes the ancestor node (immediate predecessor) of node k_t, $A_{k_t t}$ and b_{k_t} denote the coefficient matrix and right-hand-side vector values in node k_t at stage t, respectively. For each node of the scenario tree at stage t, an entire set of decision variables corresponding to that stage is introduced; for instance the vector of the first-stage decision variables X_1 corresponds to the root, and sub-vectors X_{k_t} of the t^{th} stage decision variables are assigned to the node k_t. At each stage, the sub-vectors of decision variables exploit only the information that comes from the previous stages (preceding nodes of the tree) and the choice of decisions are based on the available and past information and at the same time allow for the continuation of the decision process at the subsequent stages. It can also be observed that the NAC is implicit in this formulation. It should be noted that, if the stages in the scenario tree do not correspond to time periods, each constraint in model (1) should be repeated for all time periods at each stage.

Chapter 3

Integrated Forest Biorefinery Network Design

This chapter is dedicated to the article entitled "*Integrated Forest Biorefinery Network Design*". This article was published in the proceedings of the *7th International Conference on Information Systems, Logistics and Supply Chain* in July 2018. The titles, figures, and mathematical formulations have been revised to keep the coherence through the manuscript.

Abstract

Canadian pulp and paper (P&P) industry has been recently confronted by shrinking markets and tighter profit margins. Transforming P&P mills into Integrated Forest Biorefineries (IFBR) is one of the most prominent solutions to ensure the sustainability of this industry in the new business ecosystem. The IFBR will allow the diversification of products towards the prominent bioproducts/bioenergy markets. We propose a mixed integer programming model for IFBR network design to optimize the investment plan in addition to procurement, production and flow decisions. We test the model using a realistic case study for Canadian P&P companies, where we perform a set of sensitivity analysis tests in terms of demand quantities and energy prices. Our computational experiments showcase the potential of the IFBR transformation strategy to help P&P industry in dealing with shrinking markets for paper products. Further, the sensitivity analysis results highlight the substantial impact of the bio-product demand on the IFBR profitability.

3.1 Introduction

Over the last decade, the Canadian Pulp and Paper (P&P) industry has been confronted by the decline in the demand of conventional P&P products due to the digitalization of paper-based media, low-cost global competition from emerging economies and excess global supply of their products [22]. The sustainability of this business, hence, relies on transformation towards more diversified products and markets [10]. One of the most prominent transformation strategies would be the integration of bioproducts and the inclusion of high-value-added products in their product portfolio [23]. This will transform conventional P&P mills into Integrated Forest Biorefineries (IFBR) that relies on the transformation of biomass resources, such as forest residues, and the byproducts of P&P production processes to a range of biochemicals, biofuels, and bioenergy [24].

Although the IFBR transformation is one of the most promising strategies for P&P industry, the implementation of such a strategy is a very complex project as it involves product portfolio decisions, investment planning, technology selection, production planning, and market selection [15]. All these aspects are interrelated and interdependent which means that they should be considered with a holistic approach that will ensure the success of the implementation [25]. Furthermore, the planning approach must take into consideration future uncertainties in terms of supply, demand, energy prices, technology maturity, and government incentives.

Numerous opportunities that the IFBR offers to P&P companies lead many researchers to study this transformation and contribute to the success of this strategy (see e.g. [26-29]). Several authors looked into the product portfolio design and the selection of bioproducts to be adopted by the P&P companies via exploring the accessible biomass in different regions, the availability of reliable production technologies, and the proximity of the demand markets; to make decisions regarding the product portfolio design [12, 26]. Product portfolio and the supply chain design is addressed in [27] by the aid of a systematic decision making framework; nevertheless, the proposed approach does not employ any mathematical programming approach. On the contrary, other papers propose mathematical models to optimize the configuration of biorefinery supply chains. The model proposed in [28] approaches the problem as a network design problem by including decisions regarding capacities to be installed at each facility. A mathematical programming model was proposed in [8] that incorporates investment planning decisions for IFBR transformation where alternative investment options are financially analyzed. Various sources of uncertainty, on the other hand, affect the transformation decisions and the performance of the IFBR [12, 14]. A review of the uncertainties in biorefinery supply chains is presented in [14]. The authors in [29] discuss the addition of metrics to quantify both the flexibility and robustness of forest biorefinery supply chain.

In this study, we aim to develop a mixed integer programming model as an investment planning and network design tool for the IFBR transformation of Canadian P&P industry. The model identifies the optimal product portfolio, technology and capacity selection/timing, selection of biomass sources, along with production planning in IFBR value chain. Then we aim to identify the sensitivity of the model to changes in demand quantities and changes in energy prices. This will help future works develop a model that explicitly incorporates uncertainty in IFBR planning and network design.

The remainder of the paper is organized as follows. In Section 3.2, we briefly introduce the IFBR and elaborate on the context of the study along with the selection of technological configurations. Section 3.3 provides the deterministic mathematical model. Section 3.4 details the design of the computational experiments, followed by the results and discussion in section 3.5. Concluding remarks are provided in Section 3.6.

3.2 IFBR value netwrok

The IFBR allows P&P companies to produce bioproducts as well as P&P products via exploiting the available mill infrastructure and space for technological implementations. The type of products that can be produced at the IFBR depends on the available biomass, feasible technologies, and proximity to markets. The first important task in this integration revolves around the identification of feasible technological configurations. Since our case study is a P&P company in the province of Quebec (Canada), we will only consider the feasible configurations in the region. The biomass types abundantly available in the region incorporate: forest, agriculture, and industrial residues in addition to municipal urban wastes.

We confine our attention to the technologies that have been proven profitable and efficient in the context of North America while being compatible with the available biomass resources. More specifically, we consider: Fermentation to produce Bioethanol, Pelletization to produce Pellets, Digestion to produce Synthetic Natural Gas (SNG), and Cogeneration to produce Electricity. We also consider one byproduct generated by the process of Fermentation (i.e., Lignin) that is marketable. The integration of the biorefinery with the P&P mill will be beneficial to both. The P&P activities produce byproducts that can be used as input to the biorefinery activities; two byproducts, in particular, are considered: Black Liquor and Paper Sludge. On the other hand, the electricity generated by cogeneration in the biorefinery can be used to power the P&P mill activities. For more details about IFBR integration, the reader is referred for example to [8, 11].

3.3 IFBR network design model

Based on the feasible technological configurations identified in Section 2, we formulate a deterministic mathematical programming model that aims to optimize the investment decisions for different technologies such that the financial value of the IFBR at the end of the planning horizon is maximized. More precisely, the proposed investment plan identifies the type, capacity level, and timing of different technologies over the planning horizon. In addition, the model optimizes a set of tactical decisions in each period including quantity of each biomass type supplied, quantity of each bioproduct produced, along with the flow of biomass, byproducts, and bioproducts within the IFBR and markets. Finally, the model will decide whether or not it would be profitable to halt the P&P activities at a certain period or periods. The financial value of the IFBR at the end of the planning horizon is evaluated using a detailed financial analysis that takes into account cash flows, investments costs, tax rate, depreciation, and salvage value of facilities. We consider a fixed discount rate for all future cash flows to obtain their estimated net present value. The planning horizon is set to be 20 years split into 5-years cycles where the investment decisions can be made at the beginning of each cycle. This type of planning horizon setting is widely used in financial and economic reporting. Table 3.1 presents the notations used to formulate IFBR supply chain design model.

3.3.1 Mathematical programming model

Objective Function

The objective function (4) maximizes the sum of the discounted net cash flows and the estimated salvage value of the investment at the end of the planning horizon. All objective function terms are discounted using a discount rate to represent the present value of the IFBR investment. Eq. (5) represents the discounted net cash flows over the planning horizon, while Eq. (6) is the salvage value of the investment at the end of the planning horizon. Eq. (7)-(14) represent the cash flows, where (7)-(10) represent the cash flows of the P&P activity. Eq. (7)-(8) correspond to the revenue and production cost of P&P, respectively, while Eq. (9)-(10) formulate the operating cost and the closing cost of P&P activities. The next set of Eq. (11)-(14) represent, respectively, the revenue of bioproducts and byproducts, production cost, and raw material supply cost. Eq. (15)-(16) represent the proportion of discounted refundable fiscal depreciation and the discounted investment cost over the planning horizon. The second part of the objective function is the salvage value that depends on total investment cost annualized over the financial horizon (17), and the accounting depreciation of the investment (18).

$$\max \quad CF + SV \tag{4}$$

Table 3.1: List of notations of the deterministic model.

Sets/Indices	
T	Set of planning horizon in periods; index $t \in$ T
C	Set of planning horizon in cycles; index $c \in$ C
RM	Set of raw materials; index $u \in$ RM
Co	Set of byproducts; index $i \in$ Co
BP	Set of bioproducts; index $i \in$ BP
AP	Set of all products (bioproducts, P&P, byproducts); index $i \in$ AP
G	Set of technologies; index $n \in$ G
O	Set of capacity options; index $o \in$ O
S	Set of sinks in the network (technologies, P&P, markets); index $s \in$ S
Parameters	
FH	Financial horizon (period of paying debts)
EL	Economic lifetime (period of accounting depreciation)
FL	Fiscal lifetime (period of fiscal depreciation)
LP	Number of periods in a cycle
BG	Big number
TR	Tax rate
r	Discount rate
π	Fixed operating cost of P&P activities
ω	Closing cost of P&P activities
$c(t)$	The cycle where period $t \in$ T belongs to
CP	Capacity of P&P activities
$P_{i,t}$	Selling price of product $i \in$ AP in period $t \in$ T
$PC_{i,t}$	Unit production cost of product $i \in$ BP $\cup$ P in period $t \in$ T
$SC_{u,t}$	Supplying cost of biomass type $u \in$ RM in period $t \in$ T
$CA_{o,n,c}$	Investment cost of option $o \in$ O of $n \in$ G technology in cycle $c \in$ C
$K_{o,n}$	Capacity of option $o \in$ O of the technology $n \in$ G
E_n	Electrical consumption per unit of capacity for technology $n \in$ G
$\rho_{u,t,i}$	Conversion rate of biomass $u \in$ RM $\cup$ Co to bioproduct $i \in$ BP in period $t \in$ T
$\alpha_{i,j}$	Proportion of generating byproduct $i \in$ Co by producing $j \in$ BP $\cup$ P
$B_{u,t}$	Quantity of biomass type $u \in$ RM available in period $t \in$ T
$D_{i,t}$	Demand of product $i \in$ AP in period $t \in$ T
Decision variables	
$X_{o,n,c}$	= 1 if the capacity option $o \in$ O of technology $n \in$ G is implemented in cycle $c \in$ C; = 0 otherwise
Z_t	= 1 if the P&P activities are operational in period $t \in$ T; = 0 otherwise
$FB_{u,t,n}$	Flow of biomass $u \in$ RM in period $t \in$ T to technology $n \in$ G
$FC_{i,t,m}$	Flow of byproduct $i \in$ Co in period $t \in$ T to other technologies and the market $m \in$ G$\cup$M
$FP_{i,t,s}$	Flow of bioproduct $i \in$ BP in period $t \in$ T to all sinks $s \in$ S
$QP_{t,l}$	Quantity of P&P products produced in period $t \in$ T
$QB_{i,t,l}$	Quantity of bioproduct $i \in$ BP produced in period $t \in$ T
$QCo_{i,t,l}$	Quantity of byproduct $i \in$ Co produced in period $t \in$ T

$$CF = (1 - TR) \cdot (RP - PCP - FCP - CCP + RB + RCo \\ - PCB - RMC) + TR \cdot DF - InvHA \tag{5}$$

$$SV = \frac{InvH - DA}{(1+r)^T} \tag{6}$$

$$RP = \sum_{t \in T} \frac{P_p \cdot QP_t}{(1+r)^t} \tag{7}$$

$$PCP = \sum_{t \in T} \frac{PC_P \cdot QP_t}{(1+r)^t} \tag{8}$$

$$FCP = \sum_{t \in T} \frac{\pi \cdot Z_t}{(1+r)^t} \tag{9}$$

$$CCP = \sum_{t \in T} \frac{\omega \cdot (1 - Z_t)}{(1+r)^t} \tag{10}$$

$$RB = \sum_{t \in T, i \in BP} \frac{P_{i,t} \cdot FP_{i,t,M}}{(1+r)^t} \tag{11}$$

$$RCo = \sum_{t \in T, i \in Co} \frac{P_{i,t} \cdot FC_{i,t,M}}{(1+r)^t} \tag{12}$$

$$PCB = \sum_{t \in T, i \in BP} \frac{PC_{i,t} \cdot QB_{i,t}}{(1+r)^t} \tag{13}$$

$$RMC = \sum_{t \in T, i \in RM} \frac{SC_{i,t} \cdot \sum_{n \in G} FB_{i,t,n}}{(1+r)^t} \tag{14}$$

$$DF = \sum_{i=0}^{C-1} \left[\sum_{t = i \cdot LP + 1}^{T} \frac{\sum_{n \in G, o \in O} CA_{o,n,i+1} \cdot (X_{o,n,i+1} - X_{o,n,i})}{FL \cdot (1+r)^t} \right] \tag{15}$$

$$InvHA = \sum_{i=0}^{C-1} \left[\sum_{t = i \cdot LP + 1}^{T} \frac{\sum_{n \in G, o \in O} CA_{o,n,i+1} \cdot (X_{o,n,i+1} - X_{o,n,i})}{FH \cdot (1+r)^t} \right] \tag{16}$$

$$InvH = \sum_{i=0}^{C-1} \left[\sum_{t = i \cdot LP + 1}^{T} \frac{\sum_{n \in G, o \in O} CA_{o,n,i+1} \cdot (X_{o,n,i+1} - X_{o,n,i})}{FH} \right] \tag{17}$$

$$DA = \sum_{i=0}^{C-1} \left[\sum_{t = i \cdot LP + 1}^{T} \frac{\sum_{n \in G, o \in O} CA_{o,n,i+1} \cdot (X_{o,n,i+1} - X_{o,n,i})}{EL} \right] \tag{18}$$

Constraints

Constraints (19) correspond to biomass supply availability while (20) prevents the flow of incompatible types of biomass to technologies. The production receipt constraints (21) state that the quantity of bioproducts is the outcome of converting the flow of biomass and byproducts into bioproducts. (22)-(23) ensure that the flow of electricity produced by cogeneration to other technologies and P&P activities is sufficient to run implemented capacities as well as P&P activities. Constraints (24) do not allow the flow of bioproducts to exceed the quantity produced; while constraints (25)-(26) ensure that the flow of byproducts does not exceed the quantity generated by bioproduct technologies and P&P activities. Constraints (27) formulate production capacity limits, while (28) prevents the flow of products from unimplemented technologies. Constraints (29) ensure the quantity of P&P does not exceed the capacity. Constraints (30) correspond to the investment irreversibility constraint; while constraints (31)-(33) are the demand constraints. Finally, (34)-(41) are the domain constraints.

$$\sum_{n \in G} FB_{u,t,n} \leq B_{u,t} \quad \forall u \in RM, t \in T \tag{19}$$

$$FB_{u,t,n} \leq \rho_{u,t,n} \cdot BG \quad \forall u \in RM, n \in G, t \in T \tag{20}$$

$$QB_{i,t} = \sum_{u \in RM} \rho_{u,t,i} \cdot FB_{u,t,i} + \sum_{j \in Co} \rho_{j,t,i} \cdot FCj, t, i \quad \forall i \in BP, t \in T \tag{21}$$

$$FP_{Ele,t,n} \geq \sum_{o \in O} E_n \cdot K_{o,n} \cdot X_{o,n,c(t)} \quad \forall n \in G \neq Cog, t \in T \tag{22}$$

$$FP_{Ele,t,P} \geq E_P \cdot Z_t \cdot CP \quad \forall t \in T \tag{23}$$

$$QB_{i,t} \geq \sum_{s \in S} FP_{i,t,s} \quad \forall i \in BP, t \in T \tag{24}$$

$$QCo_{i,t} = \sum_{j \in BP} \alpha_{i,j} \cdot QB_{j,t} + \alpha_{i,P} \cdot QP_t \quad \forall i \in Co, t \in T \tag{25}$$

$$QCo_{i,t} \geq \sum_{m \in G \cup M} FC_{i,t,m} \quad \forall i \in Co, t \in T \tag{26}$$

$$QB_{n,t} \leq \sum_{o \in O} K_{o,n} \cdot X_{o,n,c(t)} \quad \forall n \in G, t \in T \tag{27}$$

$$FP_{n,t,s} \leq \sum_{o \in O} K_{o,n} \cdot X_{o,n,c(t)} \cdot BG \quad \forall n \in G, s \in S, t \in T \tag{28}$$

$$QP_t \leq Z_t \cdot CP \quad \forall t \in T \tag{29}$$

$$X_{o,n,c} \geq X_{o,n,c-1} \quad \forall n \in G, o \in O, c \in C \tag{30}$$

$$QP_t \leq D_{P,t} \quad \forall t \in T \tag{31}$$

$$FP_{i,t,M} \leq D_{i,t} \quad \forall i \in BP, t \in T \tag{32}$$

$$FC_{i,t,M} \leq D_{i,t} \quad \forall i \in Co, t \in T \tag{33}$$

$$X_{o,n,c} = 0, 1 \quad \forall o \in O, n \in G, c \in C \tag{34}$$

$$Z_t = 0, 1 \quad \forall t \in T \tag{35}$$

$$FB_{u,t,n} \geq 0 \quad \forall u \in RM, t \in T, n \in G \tag{36}$$

$$FC_{i,t,m} \geq 0 \quad \forall i \in Co, t \in T, m \in G \cup M \tag{37}$$

$$FP_{i,t,s} \geq 0 \quad \forall i \in BP, t \in T, s \in S \tag{38}$$

$$QP_t \geq 0 \quad \forall t \in T \tag{39}$$

$$QB_{i,t} \geq 0 \quad \forall i \in BP, t \in T \tag{40}$$

$$QCo_{i,t} \geq 0 \quad \forall i \in Co, t \in T \tag{41}$$

3.4 Computational experiments

I this section, we first provide description of the case study then we present the design of the sensitivity analysis experiment.

The case study under consideration incorporates a planning horizon of 20 years with 5-year cycles where investment decisions are made at the beginning of each cycle. The investment decisions deal with the selection and implementation timing of 4 possible biorefinery processes, described in section 3.2, each with 3 capacity options. Finally, 4 types of sources of biomass in addition to 2 byproducts for P&P activities have been considered.

To better reflect the reality and trends of the P&P industry in Canada, the case data is obtained based on reviews and reports regarding the industry in the region, specifically Canada (see [8, 10, 11]). The biomass available in the region is expected to increase from year to year; therefore, the cost of procurement is assumed to steadily decrease. The conversion rates of the biorefinery processes are assumed to have an increasing yearly trend to account for technological development and process improvement. This in turn will affect production costs which will have a decreasing yearly trend. The cost of investing in new biorefinery processes or higher capacities is also assumed to decrease as we move forward in the planning horizon assuming that the technology advances over time. The selling prices of bioproducts are assumed to rise assuming that the demand for such products will have an increasing trend in the market. P&P demand has a decreasing trend due to shrinking P&P markets.

3.4.1 Sensitivity analysis

In this section we explain the design of the sensitivity analysis experiment to be performed on the proposed deterministic model. This experiment is designed to identify the sensitivity of the model to changes in the demand quantities and the prices of energy.

Studying the impact of changes in model parameters on the profitability of the IFBR network will help determine if any of them is worth modeling as uncertain. The candidate parameters to be modeled as uncertain are the bioproducts demand quantities and the price of energy (electricity). The demand for bioproducts is highly uncertain because the bioproducts' market is relatively new which makes it volatile and unpredictable. While energy prices, which affect the production costs and the selling price of electricity generated at the biorefinery, depends on technological, environmental, and political factors which are uncertain in nature. Therefore, the sensitivity analysis will be conducted for these two parameters.

The sensitivity analysis is performed for each parameter separately and the experiment is conducted in iterations. For each iteration the parameter under consideration is changed by a certain percentage and the optimization model is run with the modified data. In this experiment, the sensitivity analysis is conducted for 10 iterations and the change in the parameters for each iteration (as percentage change in the base value) is summarized in Table 3.2. It is worth mentioning that the only difference between the iterations is the data and that the decision variables are left to be optimized by the model for every iteration.

Table 3.2: Sensitivity analysis iterations

Iteration	1	2	3	4	5	6	7	8	9	10
Change in Parameter	-50%	-40%	-30%	-20%	-10%	+10%	+20%	+30%	+40%	+50%

After the model is run with the modified data, the objective function value of the model is recorded and compared to the base objective function value. The comparison is conducted to find the percentage change in profitability using the following equation:

$\%Profit_i = \frac{|OF_i - Z|}{Z} 100$

Where $\%Profit_i$ measure the percentage change in profitability in iteration i, OF_i is the objective function value in iteration i, and Z is the objective function value under the base (unchanged) data. We take the absolute value of the difference in order to simplify the comparison. The results of the experiment are presented in the following section.

3.5 Results and discussion

In this section, we first provide the results of the optimization model using the data of the base case study. Then we present and discuss the results of the sensitivity analysis experiment. The optimization model (4)-(41) was solved using CPLEX 12.7.0.

3.5.1 Optimization model results (base case study)

The results of the model signify the substantial potential of transforming P&P mills into IFBR which has an estimated financial value of $562.110 million at the end of the planning horizon. The investment plan presented by the model proposes the progressive implementation of the bioenergy technologies by gradually adding capacities over the planning horizon. Table 3.3 summarizes the investment plan proposed by the model output.

The main reason for the progressive implementation of the capacities is the increasing trend of the demand, and the improvement of the conversion rates due to technological development. It is also important to notice that the cogeneration capacity is relatively high at the first stage which is

Table 3.3: Deterministic model results

		Cycle			
		1	2	3	4
Technology	Fermentation	60 M L	60 M L	150 M L	180 M L
	Pelletization	0	0	$60 \cdot 10^3$ Tons	$120 \cdot 10^3$ Tons
	Digestion	30 M m^3	75 M m^3	140 M m^3	140 M m^3
	Cogeneration	$480 \cdot 10^3$ Kw	$640 \cdot 10^3$ Kw	$960 \cdot 10^3$ Kw	$960 \cdot 10^3$ Kw

mainly because of the high initial price for electricity. However, the flow of electricity in the last two cycles is mainly used to run the bioproducts technologies as it is more profitable than just selling the electricity to the market. As for the P&P activities, the model proposes keeping the activities operational for the entire planning horizon. One of the reasons for keeping the P&P activities running even though the demand and price of P&P is declining, is the need for the byproducts generated by the P&P activities which are used as input for the production of more profitable bioproducts.

3.5.2 Sensitivity analysis results

The output of the sensitivity analysis experiment compares the percentage change in the objective function value versus the percentage change in each of the parameters under consideration separately. The first part of the analysis concerns the demand quantity, where Figure 3.1 summarizes the output of the first part.

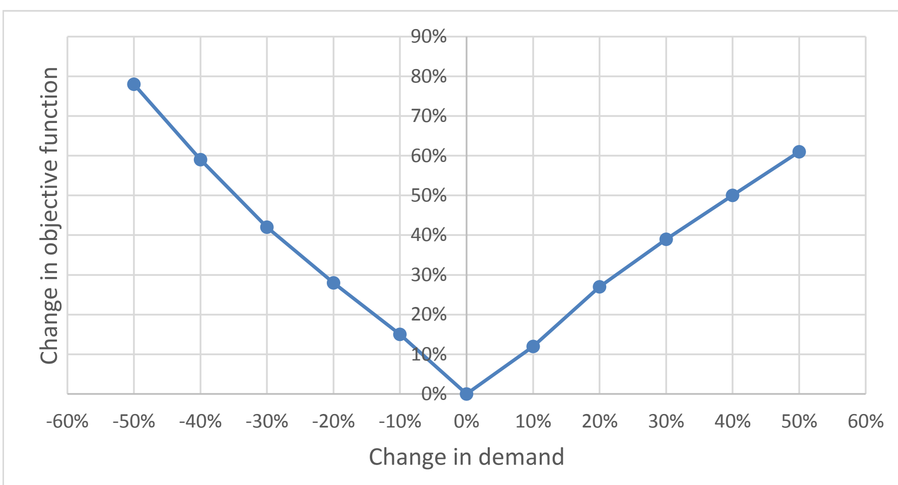

Figure 3.1: Sensitivity analysis for demand

As it is apparent from the slope of the graph in Figure 3.1, the objective function is very sensitive to change in the demand. For instance, 10% decrease in the demand results in more than 15% change in the objective function; that corresponds to 1.5% change in the profit for every 1% change in the demand. This analysis can be used to estimate how much we can afford to spend on influencing/increasing the demand using promotions or other means; because we know the expected increase in the profit as a result of the increase in demand. The second part of the analysis, sensitivity to electricity price changes, is summarized in Figure 3.2.

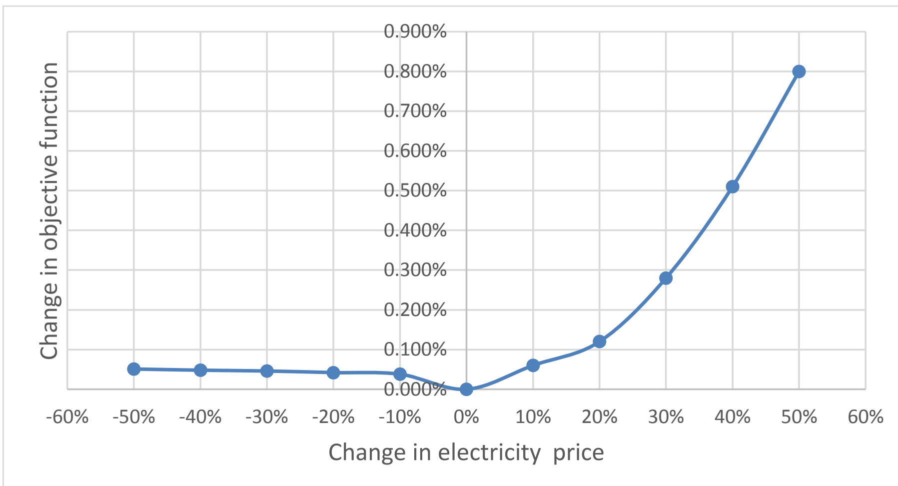

Figure 3.2: Sensitivity analysis for electricity price

The graph in figure 3.2 shows that even in the most extreme case, where the electricity price increases by 50%, the objective function value only changes by 0.8%. A possible reason for this outcome, is the fact that the results of the model show that electricity is sold to the market in the first two cycles only, while in the last two cycles the electricity is used to run the bioproducts technologies to create higher value-added products that contribute more to the value of the objective function.

The results of this experiment indicate that bioproducts demand has a substantial impact on the profitability of the IFBR network. Changes in the bioproducts market conditions could mean the success or failure of the IFBR transformation strategy. As we mentioned previously, the bioproducts demand markets are relatively new and unstable. Therefore, it is important to explicitly consider the uncertainty affecting the bioproduct demand in the IFBR network design problem.

3.6 Conclusion and future work

Canadian P&P companies must reconsider their business model in order to overcome the challenges they are facing and become more sustainable and profitable. The IFBR transformation strategy is one of the most prominent solutions to the problems facing the industry. To this end, we developed a deterministic mathematical programming model as a decision-support tool to aid in the implementation of the IFBR in the context of Canadian P&P industry. The model performs a detailed financial analysis of the IFBR strategy in order to propose an investment plan for the implementation of the most promising technologies over a planning period of 20 years. The output of the model proposed a progressive implementation plan that benefits from the increase in the demand and the improvement in the conversion technologies over time.

We also conducted a sensitivity analysis experiment concerning bioproducts demand and electricity prices. The analysis highlighted the substantial impact of bioproducts demand on the profitability of the IFBR network, while the impact of electricity prices was insignificant. As a result of this analysis we conclude that focusing on the uncertainty in bioproducts demand in the IFBR network design problem will aid the success of this strategy. The uncertainty in bioproducts demand must be considered explicitly in the decision making process using stochastic optimization techniques.

Future research would entail developing a stochastic programming optimization model to explicitly incorporate the uncertainty in the bioproducts demand in the IFBR network design. Furthermore, future work can be directed towards developing a simulation platform to test the IFBR investment plan in a random environment. Another interesting research avenue would be to test the value of flexibility in IFBR network planning.

Chapter 4

Integrated Forest Biorefinery Network Design Under Demand Uncertainty

This chapter is dedicated to the article entitled ”*Integrated Forest Biorefinery Network Design Under Demand Uncertainty*”. This article was submitted to the *International Journal of Production Research* in October 2019. The titles, figures, and mathematical formulations have been revised to keep the coherence through the manuscript.

Abstract

Transforming Pulp and Paper (P&P) mills into Integrated Forest Biorefineries (IFBR) is a prominent solution to save Canadian P&P industry that has been facing decline of conventional paper demand. In this study, we propose a comprehensive decision model for the design of IFBR value chains by taking the uncertain demand of bioproducts into consideration. In particular, we propose a Multi-stage Stochastic Programming (MSP) model to obtain the optimal investment plan over a long-term planning horizon in the presence of various market trends. We also develop a Monte-Carlo simulation platform to validate the proposed model and to compare its performance with alternative decision models. The proposed model is applied to a realistic case study inspired from P&P companies in Canada, where the value of incorporating the dynamic nature of uncertain demand has been estimated. Further, we elaborate on the value of considering flexibility in terms of adjusting the investment plan in response to changes in the market trends throughout the planning horizon. Our results indicate that the market trend for bioproducts has a substantial impact on the profitability of the IFBR. We also demonstrated the significant value of explicitly incorporating the uncertainty in IFBR network design as well as adapting the investment plan to the changes in the demand.

4.1 Introduction

4.1.1 Context and motivation

Over the last decade, the Canadian Pulp and Paper (P&P) industry has been confronted by the decline in the demand of conventional P&P products due to the digitalization of paper-based media, low-cost global competition from emerging economies, and excess global supply of their products [22]. According to a Delphi study conducted in [30], a panel of experts from industry, academia and industry associations agreed that the markets conditions facing P&P companies will change substantially by the year 2030; and that change will be a key issue for the industry in the near future. As a result of this economic environment and the growing challenges, P&P companies must transform their business model towards more diversified products and markets in order to survive and regain profitability [10]. One of the most prominent transformation strategies is the integration of bioproducts and the inclusion of high-value-added products in their product portfolio to access new markets and diversify away from the diminishing P&P markets [23]. This will transform conventional P&P mills into Integrated Forest Biorefineries (IFBR) that rely on the conversion of biomass resources, available to forest management companies, into a range of biochemicals, biofuels, and bioenergy [24]. Biorefineries are recognized as a key component in transitioning the forest industry to a sustainable economy by utilizing biomass to produce substitutes to petrol-base products and fuels [31].

Although the IFBR transformation is one of the most promising strategies for P&P industry, the implementation of such a strategy is rather a complex process as it involves several decision-making problems such as product portfolio selection, investment planning, technology selection, production planning, and market selection [15]. Besides, such decisions are prone to several sources of uncertainty in terms of supply, demand, energy prices, technology maturity, and government policies. In particular, the supply of biomass is cyclical and its cost is unstable which will affect the production quantities and costs. The technology used in the biorefinery is not fully mature and some of the processes are yet to be proven reliable which results in unstable conversion rates and yields. Moreover, government incentives, which are essential to develop the industry such that it could compete with petrol-based products and fuels, are not well-established yet [16]. Most importantly, the bioproduct and biofuel markets are relatively new and volatile. This significantly affects the demand and the selling prices of these products in the market [14]. Failing to incorporate demand uncertainty can have a negative consequences on the IFBR profitability; in other words, if the demand is below the predicted values, the facilities will remain idle; whereas if the demand is above the forecasted values, the companies will lose market share. Furthermore, market trends have a dynamic behavior over time; therefore, the investment plan must be flexible enough to be adjusted in response to changes in market trends.

As a consequence, the aforementioned uncertainty must be taken into consideration when designing an IFBR network. In other words, the proposed investment plan in terms of the choice of technology, in addition to other tactical decisions must be robust and flexible as the uncertain factors (such as market conditions) evolve over time. Nevertheless, to the best of our knowledge, less effort has been done in the literature in explicitly incorporating uncertainty in the IFBR network design. This motivated us to tackle the following research questions:

- How to develop a robust and flexible investment plan for the design of IFBR network by incorporating the uncertainty in the demand?
- What is the benefit of such a robust and flexible investment plan as compared with approaches where the investment plan is fixed at the beginning of the planning horizon and cannot be adjusted in response to changes in market trends?

By answering the proposed research questions, we are also able to cultivate some practical managerial insights regarding the IFBR strategy and implementation roadmap. In what follows, we first review the literature on the IFBR planning and supply chain design in the context of P&P companies; then, we summarize the contribution of the article.

4.1.2 Literature review

The numerous appealing opportunities that the IFBR transformation offers to P&P companies, motivated many researchers to study this transformation and contribute to the success of this strategy. Several works review the literature concerning the use of operations research models and methods in the design and operations of biomass supply chains, e.g., [32, 33]. The product portfolio design and the selection of bioproducts to be adopted by the P&P companies was investigated by [26] and [12]. The authors in [27] tried to tackle product portfolio design and supply chain design by proposing a decision making framework that systematically addresses both aspects without the aid of mathematical modeling. The authors in [34], tackle the biomass inventory control problem by proposing a centralised model predictive control strategy applied in sugarcane industries. While in [35], the authors looked into production planning for a biomass supply chain in the presence of seasonal markets.

Several papers proposed deterministic mathematical models to accelerate the IFBR transformation. In [28], the problem is modeled as a network design problem with additional constraints concerning biomass availability, flow conservation, production control, and demand satisfaction. This formulation also included decisions regarding capacities to be installed at each facility. The authors in [8] proposed a deterministic model that includes a detailed financial analysis in order to optimize the investment plan and the value creation network of the IFBR. Their model takes into account future trends in investment costs, conversion rates, and expected demand. The model presented in [36], integrates strategic and tactical supply chain design decisions to optimize forest-based biomass supply chains. The model is applied to a case study in British Columbia where the results highlighted the benefit of integrating strategic and tactical supply chain design decisions. In [37], the authors develop a model to optimize the sustainability of the IFBR value creation network by considering environmental life cycle assessment (LCA) in addition to economic objectives. The results of their study show that the IFBR contributes to reduction of Greenhouse gas emissions and production of clean energy, in addition to generating new revenues for P&P companies.

A review of the uncertainties in biorefinery supply chains is presented in [14], along with a summary of the approaches exploited in order to model them in this context. Bioproduct demand, biomass availability, technological development, product prices, and governmental incentives are among the mostly cited sources of uncertainty in IFBR network design problem. A number of papers have explored scenario-planning approach to model uncertainty in the P&P transformation into IFBR (see e.g. [11]). These papers developed a set of predefined scenarios in order to measure the performance of the forest biorefinery supply chain under each. Nevertheless, scenario-based approaches do not allow the model to explicitly optimize the decisions under uncertainty; it rather measures the performance of deterministic decisions under a set of scenarios. The authors in [29] investigate the importance of including metrics to quantify both the flexibility and robustness of forest biorefinery supply chain performance. The paper highlights the dynamic and volatile nature of the biorefinery supply chain, and how any long-term decisions must be flexible to react to changes in the demand levels and products prices. The authors of [38] proposed an approach for designing a biomass conversion system under different scenarios in terms of raw material prices. Their approach relies on a deterministic model that optimizes the topology of the supply chain taking into account the net annual profit and the environmental impact. The model is run for a number of price scenario and the most frequent supply chain topology among all scenarios is selected as the most flexible one. In [39], the authors account for uncertainty facing the forest biorefinery by conducting a sensitivity analysis on multiple aspects affecting the biorefinery supply chain, such as biomass availability, cost, and energy prices. In addition, the authors also develop a set of scenarios which represent optimistic, opportunistic and pessimistic viewpoints of decision makers towards risk. The aforementioned scenarios are used to test alternative supply chain designs and identify the best configuration for each viewpoint.

There are only a handful of works in the literature that explicitly consider uncertainty in the IFBR network design. The authors in [17] explored designing the forest biomass value chain while taking into account the uncertainty in energy prices and demand of biofuels. This paper develops a two-stage stochastic programming model for IFBR network design. In particular, their model obtains the optimal facility location, process/capacity selection, inventory/backorder levels, and flow in the network. Nevertheless, a two-stage stochastic programming approach relies on the assumption that uncertain parameters have a stationary behavior over time; hence it results in a single set of decisions for the entire planning horizon. This, on the contrary, does not provide the level of flexibility required in this type of volatile environment.

Although researchers and practitioners have become increasingly aware of the need to take into account uncertainties in the volatile business environment of the P&P sector and the IFBR, deterministic mathematical modeling coupled with scenario-based analysis is the most dominant approach proposed in the literature to account for uncertainties affecting the IFBR. However, only few papers have used stochastic programming to explicitly incorporate the uncertainties into investment planning in the context of the IFBR. Nevertheless, the models used in these papers are not capable of providing a flexible implementation plan that can be updated throughout the planning horizon.

4.1.3 Contribution and article outline

The existing literature gap in explicitly incorporating uncertainty in the IFBR network design problem motivated us to develop a Multi-stage Stochastic Programming (MSP) model that provides a flexible investment plan to facilitate the IFBR transformation. A unique feature of this technique is the ability to adjust/update the resulting investment plan to react to market changes which protects the plan against uncertainty in products demand. The aforementioned transformation strategy determines the optimal product portfolio, technology and capacity selection/timing, selection of biomass sources, along with the annual production plan in IFBR value chain. The goal is to maximize the expected financial value of the network over a long-term planning horizon.

Our second contribution revolves around developing a realistic Monte-Carlo simulation platform, so as to implement different transformation strategies and evaluate the value of introducing flexibility in terms of investment options over the planning horizon. More specifically, the latter simulation platform provides a realistic environment where the performance of the proposed MSP model, in terms of the expected financial value of IFBR network, is compared with a deterministic, a simple-recourse MSP, and a less-flexible MSP model. Simple-recourse MSP corresponds to an MSP where only the investment decisions are fixed at the beginning of the planning horizon and the remaining tactical decisions are updated in response to market changes. While less flexible MSP represent an MSP where the investment decisions are adjusted/updated less frequently over the planning horizon (e.g., updated twice instead of four times).

It should be noted that the MSP model provides an array of decisions for each possible state of demand in each stage of decision-making (e.g., every 5 years). As a consequence, when the proposed plan is implemented, the actual state of demand must be first determined in order to adopt the proper decision (e.g., capacity option for a given strategy). Therefore, we develop an algorithm to mimic the process of selecting the most appropriate set of decisions for every generated random demand portfolio in the simulation platform.

Finally, we analyze the performance of proposed model in the context of a Canadian IFBR network in order to draw valuable managerial insights regarding the factors that facilitates the IFBR transformation.

The remainder of the paper is organized as follows. In Section 4.2, we detail the problem description and provide its mathematical formulation. Section 4.3 presents the Monte-Carlo simulation platform. In Section 4.4 we present numerical experiments, and managerial insights. Concluding remarks and future research avenues are provided in Section 4.5.

4.2 Problem description and formulation

In this section, we first describe the IFBR network design problem. Afterward, we elaborate on the proposed approach to model the uncertainty of P&P, bioproducts, and electricity demand. Finally, we provide the multi-stage stochastic model formulation proposed for IFBR network design under demand uncertainty.

4.2.1 IFBR network

The IFBR value chain incorporates biomass suppliers at the upper echelon, P&P mills and biorefineries in the middle layer, and P&P, bioproducts, and electricity markets at the lower echelon. In the context of Canadian IFBR networks, the biomass abundantly available incorporates forest residues remaining from tree harvesting operations, agriculture residues such as corn starch and wheat straw, industrial residues such as wood chips and saw dust, in addition to municipal urban wastes. In the middle echelon, we confine our attention to the technologies that have been proven profitable and efficient in the context of North America while being compatible with the available biomass resources. More specifically, we consider the following technologies: Fermentation to produce Bioethanol (Eth); Pelletization to produce Pellets (Pel); Digestion to produce Synthetic Natural Gas (SNG); and Cogeneration to produce Electricity (Ele). We also consider one type of marketable byproduct that is generated by Fermentation, i.e., Lignin (LN). The P&P activities generate two byproducts (Black Liquor (BL) and Paper Sludge (PS)) that can be used as the input to the biorefinery activities. Furthermore, the electricity generated by cogeneration in biorefineries can be used to power the P&P mill activities. Figure 4.1 demonstrates the configuration of the IFBR network under investigation [8].

In the context of the aforementioned IFBR network, we aim to develop a mathematical programming model that determines the optimal investment decisions for different technologies, such that the financial value of the IFBR at the end of the planning horizon is maximized. More precisely, the proposed investment plan encompasses the type and capacity level of different biorefinery technologies (e.g., fermentation, Digestion, etc.) that should be implemented over the planning horizon. In addition, the model optimizes a set of tactical decisions in terms of the annual quantity of each type

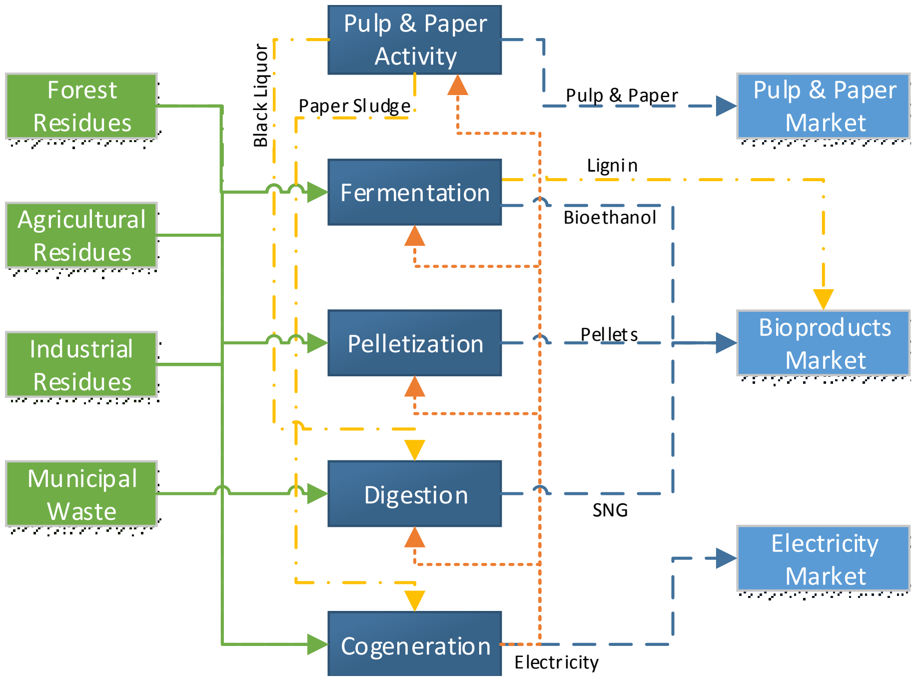

Figure 4.1: IFBR value network

of supplied biomass, the production and inventory level of P&P and bioproducts, along with the flow of biomass, byproducts, and bioproducts within the IFBR network. Finally, the model decides whether or not to halt the P&P activities at a certain period or periods in the planning horizon. The financial value of the IFBR is evaluated using a detailed financial analysis that takes into account cash flows, investment costs, tax rate, depreciation, and salvage value of facilities . We consider a fixed discount rate for all future cash flows to obtain their estimated net present value. The planning horizon is set to be 20 years split into cycles (e.g., 5 year cycles), where the aforementioned investment decisions can be updated at the beginning of each cycle. In this study, we aim to incorporate the uncertainty in the demand of P&P and bioproducts into the IFBR network design problem.

4.2.2 Modeling the demand uncertainty

We are assuming that the demand of different products in the IFBR are correlated and affected by the economic growth as well as governmental policies. Consequently, the demand is expected to follow a dynamic (non-stationary) behavior over a long-term planning horizon (e.g., 20 years). This characteristic motivated us to represent the random demand as a scenario tree. To this end, we divide the planning horizon into a number of cycles (stages), where new information on the demand (demand forecast) is revealed to the decision maker at the beginning of each stage. For instance, every 5 years, the forecasts on the economic growth and/or governmental policies are updated; hence the market trend could be better predicted. In each stage, a set of outcomes plausible to demand with their associated probabilities are defined. The latter outcomes (e.g., high/low demand) can be either defined based on experts' opinion or obtained via discretizing an underlying probability distribution fitted to historical demand data. The aforementioned procedure can be represented as a scenario tree, an example of which is depicted in Figure 4.2. In the 4-stage scenario tree depicted in this figure, each node represents an outcome of uncertain demand in each stage (cycle) and a scenario is defined as a path from the root node to each leaf node. In a scenario tree, the sum of probabilities of all nodes in each stage is equal to one and the probability of each scenario is the product of the probabilities of nodes on the path corresponding to each scenario. As mentioned earlier, a node corresponding to high demand in a given stage (e.g., node 2 in stage 2) can be interpreted as a favorable economic growth scenario; hence the maximum amount of demand for all products should be taken into consideration in IFBR network design model.

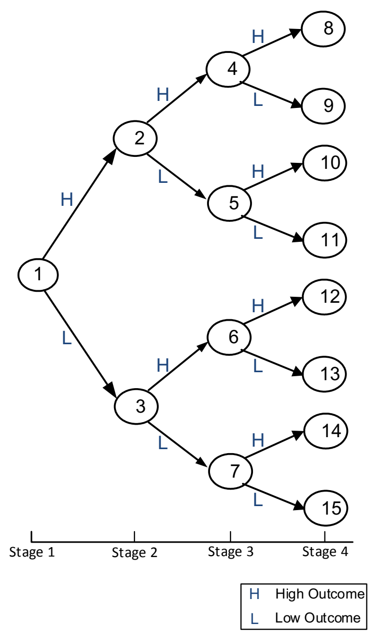

Figure 4.2: An example of a scenario tree

4.2.3 Problem formulation

According to the scenario tree representation of random demand, the IFBR network design problem can be formulated as a multi-stage stochastic program with recourse (MSP). As opposed to a deterministic formulation, where the investment decisions (i.e., opening facilities corresponding to a certain technology and capacity level of different facilities) are fixed for the entire planning horizon, the MSP modeling approach provides the flexibility in terms of the investment decisions. In other words, it provides a sequence of investment decisions that react to the outcomes of the demand in different cycles (stages) over the planning horizon. In particular, we assume that the decision maker receives a reliable forecast on the market trend for the next cycle (stage); hence the investment decisions along with halting P&P activities, and the tactical decisions can be adjusted at the beginning of each cycle for each possible outcome (node). Nevertheless, such decisions are fixed for the following cycles so as to ensure the decision maker cannot foresee the future. In other words, the non-anticipativity condition (NAC) must be taken into consideration.

The MSP model, thus, provides a comprehensive investment plan that indicates the best set of investment and tactical decisions to be implemented under each demand node in the scenario tree. For example, if the demand in the first cycle is high and at the beginning of the second cycle economic reports forecast poor economic conditions, the decision maker implements the investment decisions identified for node 5 (see Figure 4.2). The objective function of the MSP model is to maximize the expected value of IFBR over all demand nodes in the scenario tree.

The decisions are therefore indexed by the nodes while the NAC is implicitly taken into consideration. Further, constraints concerning supply, manufacturing, flow conservation, and demand are also defined for each demand node. In what follows, we provide the compact formulation of the MSP model corresponding to IFBR network design problem.

Multistage stochastic programming model

In what follows, we first provide the description of the notations which are used for sets, input parameters, and decision variables in the model. Then we present the MSP model corresponding to the IFBR network design problem.

Notations The used notations are seperated into two tables where Table 4.1 represents the sets/indices and the parameters, while Table 4.2 represents the decision variables.

In this model, there are two categories of decisions in terms of their effect period. The first category comprises of strategic decisions, which are made at the beginning of every cycle (stage) and they remain in effect (cannot be changed/updated) until the start of the next cycle. Therefore, this type of decisions are only indexed by the nodes $l \in L$ in the scenario tree. This category consists of investment decisions $X_{o,n,l}$ which set the available technologies and capacities for each cycle. The second type of decisions are tactical ones, which are made at every period (year); thus, they are indexed by both (periods $t \in T$ and nodes $l \in L$) since they are also impacted by the uncertain demand. The second category includes P&P opening/closing decisions along with the flow, production, and inventory decisions.

Objective function The objective function (42) maximizes the sum of the expected net cash flows CF and the expected salvage value SV of the investment at the end of the planning horizon. All the terms in the objective function are discounted using discount rate r to represent the present value of the IFBR investment. Equation (43) represents the expected net cash flow by multiplying the net cash flow at every node $l \in L$ by its respective probability Pr_l and summing over all the nodes in the scenario tree, plus the expected refundable fiscal depreciation, $TR \cdot DF$, minus the expected annualized investment cost over the fiscal lifetime, $InvHA$. Equation (44) is the expected salvage value of the company assets by the end of the planning horizon.

$$\text{Max} \quad CF + SV \tag{42}$$

$$CF = \sum_{l \in \mathrm{L}} Pr_l \cdot [(1 - TR) \cdot (RP_l - PCP_l - FCP_l - CCP_l +$$

$$RB_l + RCo_l - PCB_l - RMC_l - HC_l)] + TR \cdot DF - InvHA \tag{43}$$

$$SV = \frac{InvH - DA}{(1 + r)^T} \tag{44}$$

Equations (45)-(53) represent the different cash flows for the IFBR under every node $l \in L$ in the scenario tree.

Table 4.1: List of sets, indices and parameters of MSP model.

Sets/Indices	
T	Set of planning horizon in periods; index $t \in$ T
C	Set of planning horizon in cycles; index $c \in$ C
L	Set of nodes in the scenario tree; index $l \in$ L
T$_l$	Set of periods where node l is active
K$_c$	Set of nodes that belong to the same stage/cycle
RM	Set of raw materials; index $u \in$ RM
Co	Set of byproducts; index $i \in$ Co
BP	Set of bioproducts; index $i \in$ BP
AP	Set of all products (bioproducts, P&P, byproducts); index $i \in$ AP
G	Set of technologies; index $n \in$ G
O	Set of capacity options; index $o \in$ O
S	Set of sinks in the network (technologies, P&P, markets); index $s \in$ S
Parameters	
FH	Financial horizon (period of paying debts)
EL	Economic lifetime (period of accounting depreciation)
FL	Fiscal lifetime (period of fiscal depreciation)
LP	Number of periods in a cycle
BG	Big number
TR	Tax rate
r	Discount rate
π	Fixed operating cost of P&P activities
ω	Closing cost of P&P activities
CP	Capacity of P&P activities
Pr_l	The probability of node $l \in$ L in the scenario tree
$a(l)$	The ancestor node of node $l \in$ L
$c(l)$	The cycle where node $l \in$ L belongs to
$P_{i,t}$	Selling price of product $i \in$ AP in period $t \in$ T
$PC_{i,t}$	Unit production cost of product $i \in$ BP $\cup$ P in period $t \in$ T
$SC_{u,t}$	Supplying cost of biomass type $u \in$ RM in period $t \in$ T
$CA_{o,n,c}$	Investment cost of option $o \in$ O of $n \in$ G technology in cycle $c \in$ C
$K_{o,n}$	Capacity of option $o \in$ O of the technology $n \in$ G
E_n	Electrical consumption per unit of capacity for technology $n \in$ G
$\rho_{u,t,i}$	Conversion rate of biomass $u \in$ RM $\cup$ Co to bioproduct $i \in$ BP in period $t \in$ T
$\alpha_{i,j}$	Proportion of generating byproduct $i \in$ Co by producing $j \in$ BP $\cup$ P
$B_{u,t}$	Quantity of biomass type $u \in$ RM available in period $t \in$ T
$H_{i,t}$	Holding cost of product $i \in$ AP, in period $t \in$ T
$D_{i,t,l}$	Demand of product $i \in$ AP in period $t \in$ T in node $l \in$ L

Table 4.2: List of decision variables of MSP model.

Decision variables	
$X_{o,n,l}$	= 1 if the capacity option $o \in$ O of technology $n \in$ G is implemented in node $l \in$ L; = 0 otherwise
$Z_{t,l}$	= 1 if the P&P activities are operational in period $t \in$ T in node $l \in$ L; = 0 otherwise
$FB_{u,t,n,l}$	Flow of biomass $u \in$ RM in period $t \in$ T to technology $n \in$ G in node $l \in$ L
$FC_{i,t,m,l}$	Flow of byproduct $i \in$Co in period $t \in$T to other technologies and the market $m \in$G∪M in node $l \in$L
$FP_{i,t,s,l}$	Flow of bioproduct $i \in$ BP in period $t \in$ T to all sinks $s \in$ S in node $l \in$ L
$QP_{t,l}$	Quantity of P&P products produced in period $t \in$ T in node $l \in$ L
$QB_{i,t,l}$	Quantity of bioproduct $i \in$ BP produced in period $t \in$ T in node $l \in$ L
$QCo_{i,t,l}$	Quantity of byproduct $i \in$ Co produced in period $t \in$ T in node $l \in$ L
$I_{i,t,l}$	Inventory level of product $i \in$ AP in period $t \in$ T in node $l \in$ L

Equations (45)-(48) represent the cash flows of the P&P activity where (45) represents P&P products revenue, (46) represents the production cost, (47) formulates the fixed operational cost, and (48) represents the operation halting cost. The index P here represents the P&P products.

$$RP_l = \sum_{t \in \mathrm{T}} \frac{P_p \cdot QP_{t,l}}{(1+r)^t} \tag{45}$$

$$PCP_l = \sum_{t \in \mathrm{T}} \frac{PC_P \cdot QP_{t,l}}{(1+r)^t} \tag{46}$$

$$FCP_l = \sum_{t \in \mathrm{T}} \frac{\pi \cdot Z_{t,l}}{(1+r)^t} \tag{47}$$

$$CCP_l = \sum_{t \in \mathrm{T}} \frac{\omega \cdot (1 - Z_{t,l})}{(1+r)^t} \tag{48}$$

The next set of equations (49)-(52) represent the biorefinery cash flows, where equation (49) is bioproducts revenue and (50) represents the revenue from byproducts. The index M here represents the flow to the markets. Equation (51) is the production cost, and (52) is the raw material supply cost.

$$RB_l = \sum_{t \in \mathrm{T}, i \in \mathrm{BP}} \frac{P_{i,t} \cdot FP_{i,t,M,l}}{(1+r)^t} \tag{49}$$

$$RCo_l = \sum_{t \in \mathrm{T}, i \in \mathrm{Co}} \frac{P_{i,t} \cdot FC_{i,t,M,l}}{(1+r)^t} \tag{50}$$

$$PCB_l = \sum_{t \in \mathrm{T}, i \in \mathrm{BP}} \frac{PC_{i,t} \cdot QB_{i,t,l}}{(1+r)^t} \tag{51}$$

$$RMC_l = \sum_{t \in \mathrm{T}, u \in \mathrm{RM}} \frac{SC_{u,t} \cdot \sum_{n \in G} FB_{u,t,n,l}}{(1+r)^t} \tag{52}$$

Finally, equation (53) represents the inventory holding cost of all IFBR products except electricity "Ele" generated which cannot be stored and is rather sold at a lower price.

$$HC_l = \sum_{t \in \mathrm{T}, i \in \mathrm{AP}} \frac{H_i \cdot I_{i,t,l}}{(1+r)^t} \tag{53}$$

Equation (54) represents the proportion of discounted refundable fiscal depreciation annualized over the fiscal lifetime. (55) is the accounting depreciation of the investment annualized over the economic lifetime. (56) is the discounted investment cost annualized over the fiscal lifetime, and (57) is the total investment cost annualized over the fiscal lifetime. Both the accounting depreciation (55) and the annualized total investment (57) are used in calculating the salvage value which is discounted to the net present value.

$$DF = \sum_{v=0}^{C-1} \sum_{l \in \mathrm{K}_{v+1}} Pr_l \left[\sum_{v=t \cdot LP+1}^{T} \frac{\sum_{n \in G, o \in O} CA_{o,n,v+1} \cdot (X_{o,n,l} - X_{o,n,a(l)})}{FL \cdot (1+r)^t} \right] \tag{54}$$

$$DA = \sum_{v=0}^{C-1} \sum_{l \in \mathrm{K}_{v+1}} Pr_l \left[\sum_{v=t \cdot LP+1}^{T} \frac{\sum_{n \in G, o \in O} CA_{o,n,v+1} \cdot (X_{o,n,l} - X_{o,n,a(l)})}{EL} \right] \tag{55}$$

$$InvHA = \sum_{v=0}^{C-1} \sum_{l \in \mathrm{K}_{v+1}} Pr_l \left[\sum_{v=t \cdot LP+1}^{T} \frac{\sum_{n \in G, o \in O} CA_{o,n,v+1} \cdot (X_{o,n,l} - X_{o,n,a(l)})}{FH \cdot (1+r)^t} \right] \tag{56}$$

$$InvH = \sum_{v=0}^{C-1} \sum_{l \in \mathrm{K}_{v+1}} Pr_l \left[\sum_{v=t \cdot LP+1}^{T} \frac{\sum_{n \in G, o \in O} CA_{o,n,v+1} \cdot (X_{o,n,l} - X_{o,n,a(l)})}{FH} \right] \tag{57}$$

Constraints The model is subject to the constraints represented by equations (58)-(83). Constraint (58) correspond to biomass supply availability in each period while (59) prevents the flow of incompatible types of biomass to different technologies.

$$\sum_{n \in \mathrm{G}} FB_{u,t,n,l} \leq B_{u,t} \quad \forall u \in \mathrm{RM},\ t \in \mathrm{T},\ l \in \mathrm{L} \tag{58}$$

$$FB_{u,t,n,l} \leq \rho_{u,t,n} \cdot BG \quad \forall u \in \mathrm{RM},\ n \in \mathrm{G}, t \in \mathrm{T},\ l \in \mathrm{L} \tag{59}$$

The production receipt constraint (60) states that the quantity of bioproducts produced is the outcome of converting the flow of biomass and byproducts into bioproducts.

$$QB_{i,t,l} = \sum_{u \in \mathrm{RM}} \rho_{u,t,i} \cdot FB_{u,t,i,l} + \sum_{j \in \mathrm{Co}} \rho_{j,t,i} \cdot FCj, t, i, l \quad \forall i \in \mathrm{BP},\ t \in \mathrm{T},\ l \in \mathrm{L} \tag{60}$$

Constraints (61)-(62) ensure that the flow of electricity produced by cogeneration to other technologies and to the P&P activities is sufficient to run implemented capacities as well as P&P activities.

$$FP_{Ele,t,n,l} \geq \sum_{o \in \mathrm{O}} E_n \cdot K_{o,n} \cdot X_{o,n,l} \quad \forall n \in \mathrm{G} \neq Cog,\ t \in \mathrm{T}_l,\ l \in \mathrm{L} \tag{61}$$

$$FP_{Ele,t,P,l} \geq E_P \cdot Z_{t,l} \cdot CP \quad \forall t \in \mathrm{T},\ l \in \mathrm{L} \tag{62}$$

Constraints (63)-(64) prevents the flow of bioproducts from exceeding the quantity produced, where constraint (64) concerns the electricity flow and it includes excess capacity to be sold off-market $I_{Ele,t,l}$.

$$QB_{i,t,l} \geq \sum_{s \in \mathrm{S}} FP_{i,t,s,l} \quad \forall i \in \mathrm{BP} \neq Ele,\ t \in \mathrm{T},\ l \in \mathrm{L} \tag{63}$$

$$QB_{Ele,t,l} \geq \sum_{s \in \mathrm{S}} FP_{Ele,t,s,l} + I_{Ele,t,l} \quad \forall t \in \mathrm{T},\ l \in \mathrm{L} \tag{64}$$

Constraint (65) dictates the quantity of each byproduct generated by biorefinery processes and P&P activities, while constraint (66) ensures that the flow of byproducts does not exceed that generated quantity.

$$QCo_{i,t,l} = \sum_{j \in \text{BP}} \alpha_{i,j} \cdot QB_{j,t,l} + \alpha_{i,P} \cdot QP_{t,l} \quad \forall i \in \text{Co},\ t \in \text{T},\ l \in \text{L} \tag{65}$$

$$QCo_{i,t,l} \geq \sum_{m \in \text{G} \cup M} FC_{i,t,m,l} \quad \forall i \in \text{Co},\ t \in \text{T},\ l \in \text{L} \tag{66}$$

Constraint (67) formulates production capacity limits, while (68) prevents the flow of products from technologies that had not been implemented yet. Constraint (69) ensures the quantity of P&P produced does not exceed the capacity.

$$QB_{n,t,l} \leq \sum_{o \in \text{O}} K_{o,n} \cdot X_{o,n,l} \quad \forall n \in \text{G},\ t \in \text{T}_l,\ l \in \text{L} \tag{67}$$

$$FP_{n,t,s,l} \leq \sum_{o \in \text{O}} K_{o,n} \cdot X_{o,n,l} \cdot BG \quad \forall n \in \text{G},\ s \in \text{S},\ t \in \text{T}_l,\ l \in \text{L} \tag{68}$$

$$QP_{t,l} \leq Z_{t,l} \cdot CP \quad \forall t \in \text{T},\ l \in \text{L} \tag{69}$$

Constraint (70) correspond to the investment irreversibility constraint in biorefinery technologies.

$$X_{o,n,l} \geq X_{o,n,a(l)} \quad \forall n \in \text{G},\ o \in \text{O},\ l \in \text{L} \tag{70}$$

The next set of constraints (71)-(74) are the demand and inventory balance constraints, where q is equal to the ancestor of node $l \in L$ (i.e., $a(l)$) if t is the first period of each stage (cycle) and is equal to l otherwise.

$$QP_{t,l} - I_{P,t,l} + I_{P,t-1,q} \leq D_{P,t,l} \quad \forall t \in \text{T},\ l \in \text{L},\ q = \begin{cases} a(l) & \text{if } t-1 \notin c(l) \\ l & \text{if } t-1 \in c(l) \end{cases} \tag{71}$$

$$FP_{i,t,M,l} - I_{i,t,l} + I_{i,t-1,q} \leq D_{i,t,l}$$
$$\forall i \in \text{BP} \neq Ele, t \in \text{T}, l \in \text{L}, q = \begin{cases} a(l) & \text{if } t-1 \notin c(l) \\ l & \text{if } t-1 \in c(l) \end{cases} \tag{72}$$

$$FP_{Ele,t,M,l} \leq D_{Ele,t,l} \quad \forall t \in \mathrm{T}, l \in \mathrm{L} \tag{73}$$

$$FC_{i,t,M,l} - I_{i,t,l} + I_{i,t-1,q} \leq D_{i,t,l}$$
$$\forall i \in \mathrm{Co}, t \in \mathrm{T}, l \in \mathrm{L}, q = \begin{cases} a(l) & \text{if } t-1 \notin c(l) \\ l & \text{if } t-1 \in c(l) \end{cases} \tag{74}$$

The last set of constraints, (75)-(83) are the domain and non-negativity constraints.

$$X_{o,n,l} = 0, 1 \quad \forall o \in \mathrm{O},\ n \in \mathrm{G},\ l \in \mathrm{L} \tag{75}$$

$$Z_{t,l} = 0, 1 \quad \forall t \in \mathrm{T},\ l \in \mathrm{L} \tag{76}$$

$$FB_{u,t,n,l} \geq 0 \quad \forall u \in \mathrm{RM},\ t \in \mathrm{T},\ n \in \mathrm{G},\ l \in \mathrm{L} \tag{77}$$

$$FC_{i,t,m,l} \geq 0 \quad \forall i \in \mathrm{Co},\ t \in \mathrm{T},\ m \in \mathrm{G} \cup M,\ l \in \mathrm{L} \tag{78}$$

$$FP_{i,t,s,l} \geq 0 \quad \forall i \in \mathrm{BP},\ t \in \mathrm{T},\ s \in \mathrm{S},\ l \in \mathrm{L} \tag{79}$$

$$QP_{t,l} \geq 0 \quad \forall t \in \mathrm{T},\ l \in \mathrm{L} \tag{80}$$

$$QB_{i,t,l} \geq 0 \quad \forall i \in \mathrm{BP},\ t \in \mathrm{T},\ l \in \mathrm{L} \tag{81}$$

$$QCo_{i,t,l} \geq 0 \quad \forall i \in \mathrm{Co},\ t \in \mathrm{T},\ l \in \mathrm{L} \tag{82}$$

$$I_{i,t,l} \geq 0 \quad \forall i \in \mathrm{AP},\ t \in \mathrm{T},\ l \in \mathrm{L} \tag{83}$$

4.3 Monte-Carlo simulation platform

In this section we elaborate on the details of the Monte-Carlo simulation platform developed in order to realistically compare the performance of the investment plans proposed by different IFBR network design models such as deterministic, simple-recourse multi-stage stochastic program (MSP), a 3-stage, and 5-stage stochastic programs (SP). While the deterministic model considers one demand profile over the planning horizon, the simple-recourse MSP, 3-stage, and 5-stage SP models take into account the uncertain demand, modeled as a scenario tree. Nevertheless, the investment decisions are not flexible in the simple-recourse MSP model. In other words, the investment decisions $X_{o,n,l}$ are all identical for all nodes in each stage (cycle) in the scenario tree. Finally, the 3-stage SP model is less flexible as compared with the 5-stage model in the sense that it provides the possibility of updating the investment plans in 10-year cycles as opposed to the 5-year cycles in the latter model.

The simulation platform involves two major steps, including "scenario generation" and "implementation" phases. In the scenario generation phase, random scenarios in terms of the quantity of demand for different products in each period of the planning horizon are generated according to a given probability distribution. Afterwards, the "implementation" phase replicates the implementation of an investment plan proposed by a given decision model (e.g., deterministic, simple recourse MSP, 3-stage, and 5-stage SP) for each of the randomly generated demand scenarios. To this end, the investment plan (represented by the investment decision variables $X_{o,n,l}$) and each demand scenario are plugged into a deterministic model, denoted as "*DetModel*". This model is similar to model (42)-(83), except that there exist only one node in each stage. Afterwards, this model is solved to obtain the optimal financial value of the IFBR network. This process is repeated for a number (*N*) of randomly generated scenarios and the expected financial value is calculated for all *N* replications. The summary of the proposed Monte-Carlo simulation process is provided in Algorithm 1.

Algorithm 1 Simulation Process

```
while Number of scenarios generated ≤ N do
    Step 1:
    Generate random demand scenario from the given probability distribution
    Step 2:
    if The plan corresponds to the deterministic or simple-recourse MSP models then
        Plug investment decisions (X_{o,n,l}) directly into "DetModel"
    else   [MSP plan]
        Use the "Decision implementation" algorithm (Algorithm 2)
    end if
    Step 3:
    Run DetModel with the generated scenario
    Record the objective function (financial value)
end while
Step 4:
Calculate the expected financial value over the N generated scenarios
```

Given that the 3-stage and 5-stage SP models provide investment plans for each demand outcome (node) in the scenario tree, in order to simulate the implementation of the plan, we first need to identify the demand nodes (e.g., high or low) that represents the randomly generated demand scenario over the planning horizon. Afterwards, the decisions associated to those node are plugged in the "*DetModel*" in order to calculate the financial value of IFBR under each demand scenario. We denote this process as "*Decision implementation*" that is summarized in Algorithm 2.

Algorithm 2 Decision Implementation

Step 1:
Categorize the randomly generated demand into *High* or *Low* using threshold value {
for Every cycle in the planning horizon **do**
    if Average demand of periods in the cycle $\geq$ treshold value **then**
        Demand is *High*
    else
        Demand is *Low*
    end if
end for }
Step 2:
Convert the sequence of categorized demand into the corresponding active node in each cycle (stage) of the scenario tree
Step 3:
Plug investment decisions representing these nodes in "*DetModel*"

The decision implementation algorithm uses threshold values to determine if the randomly generated demand at each cycle represents High or Low nodes. After setting the threshold, the algorithm looks at the average demand over all the periods in each cycle in order to categorize the demand into high or low. The results of the first step is a sequence of outcomes (high/low), which is used in the second step to identify the corresponding node in each stage of the scenario tree. Finally, the algorithm selects the investment decisions corresponding to the identified nodes and plugs them in the "*DetModel*", before continuing with step 3 of the simulation process (Algorithm 1).

4.4 Computational experiments

In this section, we first elaborate on a case study in the context of Canadian P&P companies that has been exploited in order to validate the proposed IFBR network design model. Afterwards, we provide the details of the designed numerical experiments followed by the analysis of the numerical results.

4.4.1 Case study

The case study under consideration incorporates a planning horizon of 20 years with 5-year cycles where investment decisions are made at the beginning of each cycle. The investment decisions deal with the selection and implementation timing of 4 possible biorefinery processes, described in section 4.2.1, each with 3 capacity options. Finally, 4 types of sources of biomass in addition to 2 byproducts for P&P activities have been considered.

To better reflect the reality and trends of the P&P industry in Canada, the case data is obtained based on reviews and reports regarding the industry in the region, specifically Canada (see [8, 10, 11, 12, 14, 15, 16, 23, 26]). The biomass available in the region is expected to increase from year to year; therefore, the cost of procurement is assumed to steadily decrease. The conversion rates of the biorefinery processes are assumed to have an increasing yearly trend to account for technological development and process improvement. This in turn will affect production costs which will have a decreasing yearly trend. The cost of investing in new biorefinery processes or higher capacities is also assumed to decrease as we move forward in the planning horizon assuming that the technology advances over time. The selling prices of bioproducts are assumed to rise assuming that the demand for such products will have an increasing trend in the market. The demand of both P&P and bioproducts is assumed to follow a uniform distribution; however, P&P demand has a decreasing trend due to shrinking P&P markets.

We consider 2 possible outcomes for the demand (high and low) with equal probabilities in each stage of the scenario tree. This leads to a 5-stage scenario tree that contains a total of 31 nodes and 16 scenarios. The mathematical model is implemented in CPLEX Optimization Studio 12.7.0.

4.4.2 Experimental design

In this section, we first explain the sensitivity analysis experiments designed in order to investigate the impact of the different demand trends on the performance of 5-stgae SP model proposed for IFBR network design. Afterwards, we present the details of Monte-Carlo simulation experiments designed to measure the value of flexibility in terms of investment plans while designing a strategy towards IFBR transformation of Canadian P&P industry.

Design of sensitivity analysis experiment

We perform a set of sensitivity analysis experiments on the 5-stage SP model under different market conditions for both bioproducts and P&P. The goal is to investigate the impact of different market conditions for the aforementioned products on the financial value of the IFBR network.

In these experiments, we consider four different market conditions (i.e., poor, average, good, and excellent), where each has a distinct effect on the demand of bioproducts and P&P. Table 4.3 summarizes the market conditions and their effect on the demand of P&P and bioproducts. Recall from section 4.2.2, that the demand scenario tree contains two nodes in each stage (low/high). In this table, the first term in the bracket represents the low demand while the second term represents the high demand outcome, both presented as a percentage change (decrease/increase) in the average demand in each stage. For instance, under poor market conditions, the bioproducts demand is expected to increases by 10% and 30% of the average demand under low and high demand scenarios, respectively. On the contrary, the demand for P&P is expected to decrease by 80% and 40% under low and high demand scenario, respectively.

Table 4.3: Market conditions for bioproducts and P&P.

Market conditions	Bioproducts demand trends (Low, High)	P&Pdemand trends (Low, High)
Poor	(+10%, +30%)	(-80%, -40%)
Average	(+20%, +50%)	(-70%, -30%)
Good	(+30%, +70%)	(-50%, -20%)
Excellent	(+50%, +90%)	(-30%, +10%)

Afterwards, we generate sixteen stochastic settings (i.e., 16 scenario trees) represented as the combination of market condition for P&P and bioproducts. For example, one stochastic setting is comprised of excellent market conditions for bioproducts and average market conditions for P&P; while another setting has average market conditions for both product types. This will helps us capture a multitude of possible stochastic environments and to investigate their impact on the IFBR network design model. In particular, our goal is to clarify which category of the products (P&P or bioproducts) has a greater impact on the profitability of IFBR. Further, we estimate the value of stochastic solution (VSS) for the aforementioned stochastic settings via comparing the expected financial value of the deterministic IFBR network design with the one determined by the MSP model under each stochastic setting.

Design of simulation experiment

Our main objective in this set of experiments is to assess the value of incorporating the random and dynamic behavior of demand in IFBR network design problem. To this end, we compare 4 investment plans proposed by a deterministic, a simple-recourse MSP, along with a 3-stage and a 5-stage SP models. Our first goal is to measure the value of stochastic solution in a more realistic manner. Our second goal is to measure the ability of the model to adapt the investment plan as new information is revealed to the decision maker over the planning horizon. Finally, we aim to investigate the value of increasing the level of flexibility in the MSP model. While updating the decisions more frequently offers more flexibility, it increases the model complexity. This experiment will help identify the trade-off between the complexity and the benefit of more flexible models.

This experiment will utilize the Monte-Carlo simulation platform presented in section 3 to calculate the expected financial value of each investment plan over a total of 100 randomly generated demand scenarios. The financial value of each plan will be compared to the others using $Gap(\%)$.

4.4.3 Results and discussion

In this section, we first provide the sensitivity analysis results on the 5-stage SP model under different stochastic settings, followed by Monte-Carlo simulation results.

Sensitivity analysis results

After running the 5-stage SP model for the 16 stochastic settings, described in section 4.4.2, we noticed that the model proposes a progressive implementation strategy for different technologies in terms of their production capacities over the planning horizon. The main reason behind the incremental capacity increase is the increasing trend of the bioproducts demand and the improvement in conversion rates due to technological development over the planning horizon. It is also important to note that the cogeneration capacity is relatively high in the first cycle in most cases which is mainly because of the high initial price of electricity as well as the demand of biorefinery and P&P activities for electricity. On the contrary, the flow of electricity in the last two cycles is mainly used to run the biorefineries. In other words, producing electricity for biorefinery consumption is more profitable than selling it on the market. As for the P&P activities, in high-demand stochastic settings, the model is choosing to run the P&P activities for the entire planning horizon. However, in low-demand stochastic settings, the model is halting P&P activities for some periods while using the accumulated inventory to satisfy the demand for the periods with no production. Nevertheless, the model still choose to completely halt the P&P operations for the last cycle in some of the poor-demand stochastic settings.

In order to compare the sensitivity of the 5-stage SP model to the demand of bioproducts and P&P, the expected financial value of IFBR strategy are reported separately in Figures 4.3 and 4.4. More specifically, in Figure 4.3, the expected financial value of IFBR (in million dollars) is plotted separately for stochastic settings that correspond to poor, average, good, and excellent P&P market conditions. The horizontal axis in Figure 4.3 represents different market conditions for bioproducts. Figure 4.4, on the contrary, provides the financial value plots for different bioproducts demand conditions under different P&P market trends.

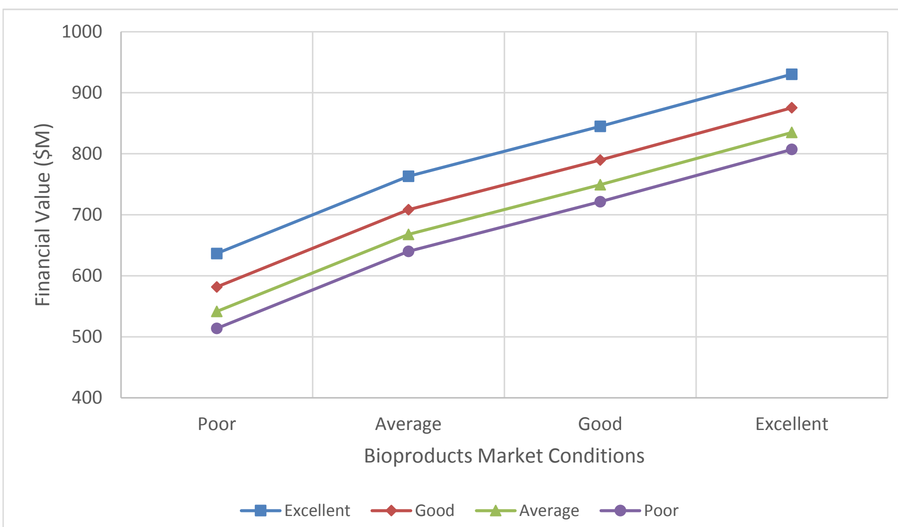

Figure 4.3: Effect of changes in P&P market conditions

As it can be observed in Figure 4.3, the changes in the P&P demand conditions does not have a significant impact on the financial value of the IFBR under different bioproduct demand trends (the lines are close to each other). On the contrary, Figure 4.4 clearly indicates that the changes in bioproducts demand have a substantial impact on the financial value of IFBR (the gap between the lines is larger).

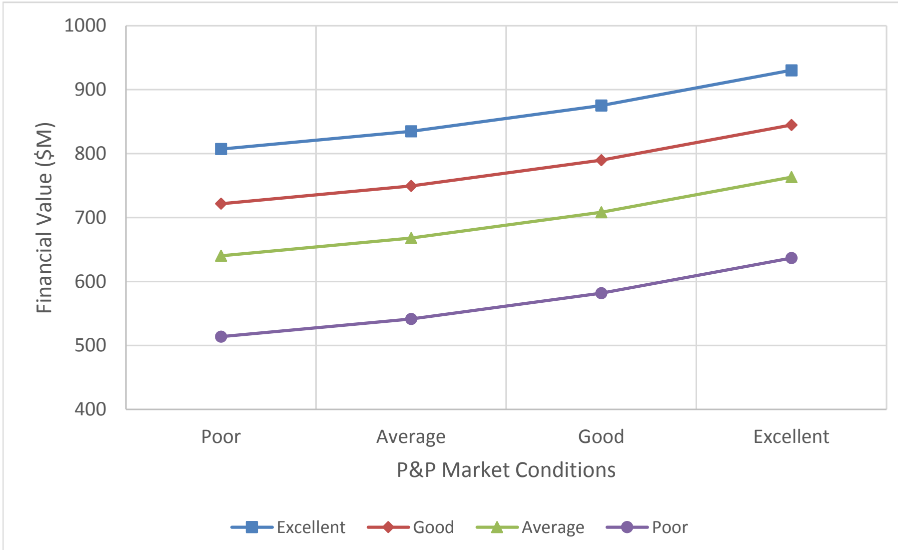

Figure 4.4: Effect of changes in Bioproducts market conditions

The above-mentioned results highlight the impact of changes in bioproducts markets on the profitability of the IFBR. This motivated us to estimate the value of further investments in the promotion and advertisement of bioproducts so as to increase their demand in the market. For instance, based on the results provided in Figure 4.3, considering the line that represents excellent market conditions for the P&P products, the difference between the first point (poor market conditions for bioproducts) and the next point (average market conditions for bioproducts) is around 125 M$; which means that influencing the bioproducts market conditions to improve from poor to average is worth 125 M$. Thus, setting a promotional budget of less than 125 M$ in this case is expected to provide a positive impact on the profitability of the IFBR transformation for P&P industry.

The value of stochastic solution

In this section, we compare the expected financial value of the investment plan proposed by the deterministic and 5-stage SP models for the 16 stochastic settings described in section 4.4.2. More specifically we aim to measure the value of stochastic solution (VSS) under the aforementioned settings. To this end, we plug the investment decisions of the deterministic solution into the 5-stage stochastic model in order to obtain the expected financial value of the IFBR. We denote this value as the expected value of deterministic solution (EDS). VSS is then calculated as the difference between EDS and the objective function value of MSP model. The results are summarized in Figure 4.5, where the EDS, MSP, and $VSS(\%)$ are reported separately. $VSS(\%)$ is calculated using the following equation:

$$VSS(\%) = \frac{MSP - EDS}{MSP} 100.$$

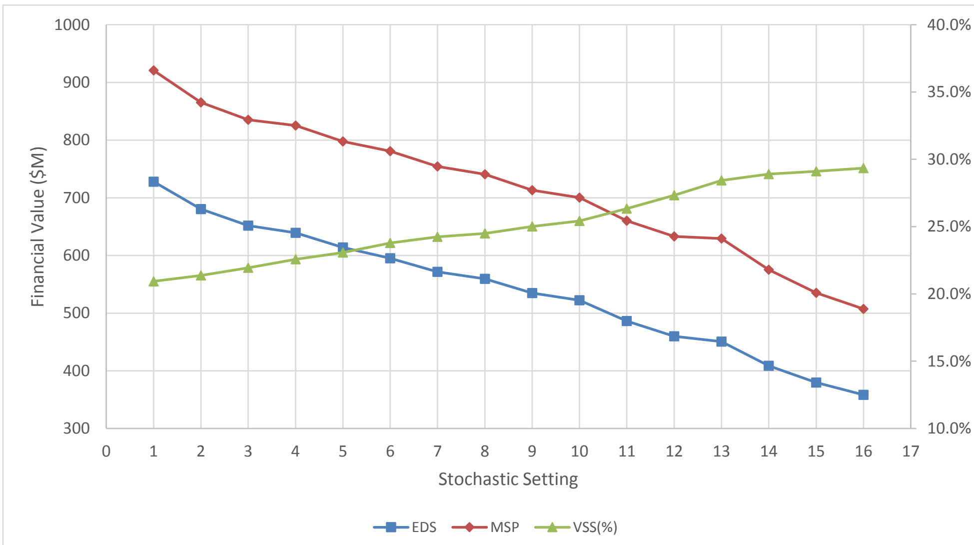

Figure 4.5: Value of stochastic solution

The comparison between the EDS and MSP graphs in Figure 4.5 indicates that the MSP results in a higher expected financial value as compared with the deterministic solution over all stochastic settings. The results show that this gap is around 177 M$ on average over all settings. This highlights the advantage of the MSP model over a deterministic approach under a dynamic and uncertain demand environment. Furthermore, the $VSS(\%)$ shows an increasing trend as we moves towards stochastic settings with poor market conditions. More precisely, the results indicate that the $VSS(\%)$ under the first stochastic setting, which corresponds to excellent market conditions for both P&P and bioproducts, is around 21%. Whereas, under the last stochastic setting, which corresponds to the poor market conditions for both product types, the $VSS(\%)$ is 29%. This clearly shows that the performance of the deterministic solution deteriorates faster under poor market conditions as opposed to good market trends for both category of products.

The main reason for superiority of the MSP solution is the flexibility offered by this approach to update the investment plan at every stage (cycle) as a response to each demand outcome. The deterministic approach, on the contrary, provides a single investment plan regardless of future changes in products demand.

Simulation results

In this section, we compare the performance of the investment plans proposed the deterministic, simple-recourse MSP, 3-stage, and 5-stage SP models by utilizing the Monte-Carlo simulation platform presented in section 4.3. The main outcome of the simulation is the expected financial value of the IFBR over all the simulation iterations for each investment plan. The aforementioned plans are compared via measuring the $Gap(\%)$ using the following equation:

$$Gap(\%) = \frac{FVPA - FVPB}{FVPA}100$$

Where, $FVPA$ denotes the financial value of the IFBR for the plan under consideration (e.g., 5-stgae SP) and $FVPB$ represents the financial value of the IFBR under other plans (e.g., 3-stage SP, simple-recourse MSP, or deterministic). The comparison of the tested investment plans is summarized in Figure 4.6.

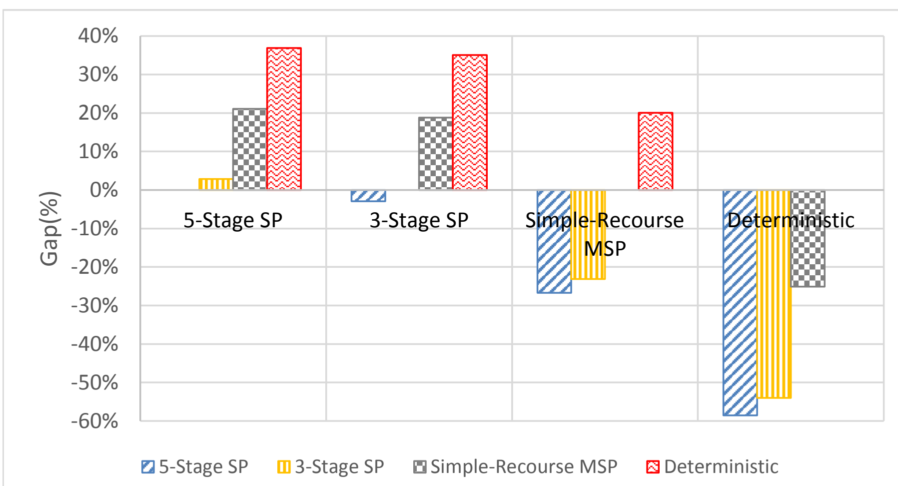

Figure 4.6: Comparison of investment plans performance

According to the results in Figure 4.6, the investment plan proposed by the simple-recourse MSP outperforms the deterministic plan by a $Gap(\%)$ of 20%. This shows the importance of explicitly considering the uncertainty in the IFBR network design model. Furthermore, the results indicate that the investment plans proposed by the 3-stage and 5-stage SP models are far more superior to the simple-recourse MSP plan ($Gap(\%)$ of 19% and 21%, respectively). This highlights the advantage of updatable IFBR investment plans as more information on the market trends become available to the decision maker.

Nevertheless, the 3-stage and 5-stage SP models are featured with higher computational complexity in the sense that they contain more decision variables as compared with a simple-recourse MSP model. Furthermore, the plans proposed by these models are more demanding to implement given that the 3-stage and 5-stage SP models provide an array of technological options for different nodes (different market trends) in the scenario tree, while the simple-recourse approach provides one set of investment decisions over the planning horizon.

Finally, when comparing the performance of the investment plans proposed by the 3-stage and the 5-stage SP, we can see that the $Gap(\%)$ is around 2.8%, which is equivalent to 15M$ in terms of the value of the IFBR network. The ability to update investment decisions more frequently in the 5-stage model (every 5 years as compared with 10 years in the 3-stage SP plan) is the main contributor to this performance gap. Nonetheless, we also notice the incremental impact of adding flexibility in the investment plans which indicates that shortening the length of investment cycles further would probably result in a marginal improvement in terms of financial value of IFBR.

4.5 Conclusion and future work

Transforming P&P mills into an IFBR is a complex project that has potential to improve profitability and sustainability of P&P companies that are currently struggling with challenging market conditions. One of the key factors that complicates this transformation is the uncertainty regarding the demand of bioproducts. Given the paucity of research on incorporating the uncertainty into the design of IBBR value chains, we filled the void by modeling this problem as a multi-stage stochastic program. This model optimizes the IFBR investment decisions in terms of the choice and capacity level of various biorefinery technologies as well as tactical decisions in the network. The demand uncertainty was modeled as a scenario tree and a Monte-Carlo simulation platform was developed to test the validity of proposed investment plans in a random and realistic environment.

Our numerical results on a real case study in the context of Canadian P&P sector shed light to several interesting managerial insights as follows:

- The bioproducts demand has a substantial impact on the financial value of the IFBR, whereas the impact of P&P demand is less influential. This indicates that the rapid decline in the demand of P&P products can be mitigated by diversifying away from this market and focusing on bioproducts.
- The results highlight the importance of investing in bioproducts instead of investing in modernizing conventional P&P technologies. This would suggest to foresee a budget of advertisement for promoting bioproducts in the market given the more significant impact of the demand for such product on the financial viability of IFBR.
- The comparison between the financial value of IFBR corresponding to the MSP network design model with a deterministic approach clearly indicates the importance of incorporating uncertainty into decision models given the volatile nature of business environment in this industry. This impact, in particular, is more significant under poor market conditions for P&P and bioproducts.
- The simulation results confirmed the advantage of incorporating flexibility in terms of updating the investment plan as new market trends are revealed to the decision-maker over the long-term planning horizon.

Future research avenues would entail the inclusion of other sources of uncertainty that affect the IFBR such as the selling prices of bioproducts, raw material availability, investment risks, in addition to uncertainty in the production conversion rates, and technology maturity. Investigating a more detailed IFBR network design problem, where decisions regarding facility type/location, modes of transportation, and other logistics aspects would be another interesting research direction. Finally, it would be beneficial to consider a measure of sustainability into the problem such that the environmental and social impacts of the IFBR transformation are also taken into consideration. This is expected to provide a more comprehensive analysis of the value of the IFBR transformation for the P&P sector.

Chapter 5

Conclusion and Future Work

5.1 Concluding remarks

In this thesis, we investigated the Integrated Forest Biorefinery (IFBR) network design under demand uncertainty in the context of Canadian Pulp and Paper (P&P) companies. The IFBR faces many sources of uncertainty as the industry goes through an unstable change period. The existing literature, explains the impact of the uncertainty on the IFBR and highlights the importance of incorporating the uncertainty in the planning process. However, most of the existing works in the literature use deterministic models coupled with scenario-based approaches to account for this uncertainty and only few works explicitly incorporate the uncertainty in IFBR network design. This motivated us to address this gap in the literature and provide an IFBR network design tool that explicitly incorporates the uncertainty facing the IFBR.

In the first part of this thesis, we proposed a mixed-integer programming model for the IFBR network design to optimize the investment plan in addition to procurement, production and flow decisions over 20-years planning horizon. This model is used as basis to develop a stochastic optimization model in the second part. We tested the model using a realistic case study in the context of Canadian P&P industry. The computational results showcased the potential of the IFBR transformation strategy to help P&P industry survive in the diminishing markets for conventional paper products. The model output proposed a progressive implementation plan that benefits from the increase in the demand and the improvement in the conversion technologies over time. Moreover, we performed a set of sensitivity experiments on the proposed model to test the impact of demand quantities and energy prices on the profitability of the IFBR. The sensitivity analysis results highlighted the substantial impact of the bio-product demand on the IFBR profitability. This indicated that incorporating the demand uncertainty in the planning process would be most beneficial for the success of the IFBR.

As the second contribution, we proposed a Multi-stage Stochastic Programming (MSP) model for the IFBR network design that incorporates the uncertainty in the bioproduct demand. The latter was modeled as a scenario tree over the planning horizon. We also developed a Monte-Carlo simulation platform to validate the proposed model and compare its performance with alternative decision models in a realistic random environment. Furthermore, we conducted computational experiments to assess the value of incorporating the dynamic nature of uncertain demand in the planning process and performed sensitivity analysis to evaluate the impact of changes in market conditions on the profitability of the IFBR. Further, we elaborated on the value of considering flexibility in terms of adjusting the investment plan in response to changes in the market trends throughout the planning horizon. Our results indicated that the market trend for bioproducts has a substantial impact on the profitability of the IFBR. We also demonstrated the significant value of explicitly incorporating the uncertainty in IFBR network design as well as adapting the investment plan to the changes in the demand.

5.2 Future research directions

Future research avenues in regards of extensions of this thesis can revolve around the following directions:

- Including other sources of uncertainty that affect the IFBR transformation, namely the price of P&P and bioproducts as well as the maturity level of different technologies.
- Expanding the proposed model to include more decisions regarding facility type/location, mode of transportation or other logistics aspects.
- Investigating the addition of other measures of sustainability to the model to account for the

environmental and social impacts of the IFBR.

- Implementation of the proposed decision models in the P&P companies located in the province of Quebec. The latter might require adjustments to the models so as to consider the specific features of each business case.

Appendix A

Case study data

The case study data is obtained based on reviews and reports regarding the P&P industry and biorefineries in the region, specifically Canada. Assumptions were also made in case of unavailable data. Table A.1 summarizes the case study data.

Table A.1: Case study data

Parameter	Index	Values	
Fiscal lifetime	FL	20 years	
Economic lifetime	EL	30 years	
Financial horizon	FH	20 years	
Tax rate	TR	30%	
Discount rate	r	5%	
Fixed oprations cost of P&P activity	π	$20 M	
Halting cost of P&P activity	ω	$10 M	
Capacity of P&P Activity	CP	130 Kt	
Selling price	$P_{i,t}$	Eth	$0.65/L
		Pel	$175/t
		SNG	$0.35/m^3
		Ele	$3.18/KW
		LN	$459/t
		Future trend	+2%/year
		P&P	$750/t -1%/year
Production cost	$PC_{i,t}$	Eth	$0.225/L
		Pel	$65/t
		SNG	$0.026/m^3
		Ele	$4.75/KW
		Future trend	-1.5%/year
		P&P	$318/t does not decrease
Supply cost	$SC_{u,t}$	FR	$740/t
		AR	$650/t
		IR	$800/t
		Future trend	-1%/year
		MW	-$15/t does not decrease
Investment costs	$CA_{o,n,c}$	Eth	$1.21/L
		Pel	$118.5/t
		SNG	$2/m^3
		Ele	$3.75/KW
		Future trend	-7.5%/cycle
Capacity options	$K_{o,n}$	Eth	30 M L / 60 M L / 90 M L
		Pel	20 Kt / 40 Kt / 60 Kt
		SNG	30 M m^3 / 45 M m^3 / 65 M m^3
		Ele	16 MW / 32 MW / 48 MW
Electricity consumption	E_n	Biotechnology	11.4 KW/unit assumption
		P&P	30.47 KW/t
Conversion rate	$\rho_{u,t,i}$	Eth	FR 2900 L/t
			AR 2700 L/t
			IP 3400 L/t
		PEL	IR 0.55 t/t
		SNG	MW 1000 m^3/t
			PS 2000 m^3/t
		Ele	FR,AR 920 KW/t
			BL 1200 KW/t
			IR 1020 KW/t
		Future trend	+0.75%/year
Co-product generation rate	$\alpha_{i,j}$	BL	P&P 0.17 t/t
		PS	P&P 0.2 t/t
		LN	Eth 0.004 Kg/L
Biomass availability	$B_{u,t}$	FR	6.4 Kt
		AR	10 Kt
		IR	5 Kt
		MW	7 Kt
		Future trend	+1%/year
Expected demand	$D_{i,t}$	Eth	22.6 M L
		Pel	10 Kt
		SNG	20 M m^3
		Ele	32 MW
		LN	8.4 Kt
		Future trend	+1.5%/year
		P&P	128.7 Kt -4%/year

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