Designing Forest Biomass Value Chain under Uncertainty

FOROOGH ABASIAN[1], MIKAEL RÖNNQVIST[2], MUSTAPHA OUHIMMOU [3]

[1] PhD Candidate, Université Laval
1065, avenue de la Médecine, Département de génie mécanique, Bureau 3511, Québec (Qc), G1V 0A6
foroogh.abasian.1@ulaval.ca

[2] Professor, Université Laval
1065, avenue de la Médecine, Département de génie mécanique, Bureau 3345, Québec (Qc), G1V 0A6
mikael.ronnqvist@gmc.ulaval.ca

[3] Professor, École de technologie supérieure
1100, rue Notre-Dame Ouest, Département de génie de la production automatisée, Bureau A-3586, Montréal (Qc), H3C 1K3
Mustapha.Ouhimmou@etsmtl.ca

Abstract – **Canadian forest industry has sought to transform its business model to help the sector adaption to new challenges. The challenges consist of a dramatic decrease in newsprint demand, non-investment at old manufacturing plants and dropping in crude-oil price. Recovering such difficult condition has required a transformation from traditional forest supply chain into new biomass value chain to use novel processes, products and markets. However, these novelties trigger several uncertainties in the network. Hence, in order to create a smooth transformation for the industry, this paper studies the design of a forest biomass value chain network considering uncertainty on energy prices and demand of biofuels. An optimization model considering strategic and tactical decisions for the value chain is developed and a two stage-stochastic optimization is employed to tackle considered uncertainties in the model. Preliminary results show that proposed model performs, in average, 8% better than the deterministic solution.**

***Keywords* –Forest biomass, network design, uncertainty.**

1 INTRODUCTION

The importance of biomass contribution for the future energy, supply in industry, transportation and residential heating, is evident for every one [Yamamoto et al., (2001), Berndes et al., (2003) and Demirbaş, (2001)]. Among potential biomass, forestry sources are very good alternatives from feasibility and environmentally point of view especially in Canada. Harvesting residues including branches and straw, non-merchantable woods and forest by-products including low quality wood chips and sawdust are some examples of forest biomass. These low value feeds could supply to new processes to produce high value products comprises bioenergy (e.g., heat and electricity), biofuels (e.g., ethanol, biodiesel and bio-gasoline) or other bio-based products (e.g., chemicals, pharmaceutics, plastics, etc.). This conversion processes could be expressly called forest biomass value chain.

Design of defined value chain is today main concern of Canadian forest industry. The complexity of this value chain alone doesn't bring its high difficulty, but its all new and uncertain design parameters play critical roles in increasing problem difficulty. For instance in each harvest area, the volume, species, and moisture of forest residues are unpredictable, hence their extracted energy which affect their price is unpredictable. The uncertainty on the technology performance is created due to their novelty and it affects the process cycle time, throughput and yield. For new products in new market the uncertainty on demand and price is an undeniable fact. Moreover, recently other logistics cost in designing a value chain such as fuel oil cost and money values have obviously fluctuated. Thus, the proficiency of forest biomass value chain owns considering the aforementioned uncertainties.

An important method for the management of forest biomass is designing its value chain. The development of a sustainable and competitive forest biomass value chain may depend on well-design biomass supply, agile technologies, and integration of conventional and novel value chain. Figure 1 shows an overall view of potential forest biomass value chain design. This forest biomass value chain comprises interrelated and

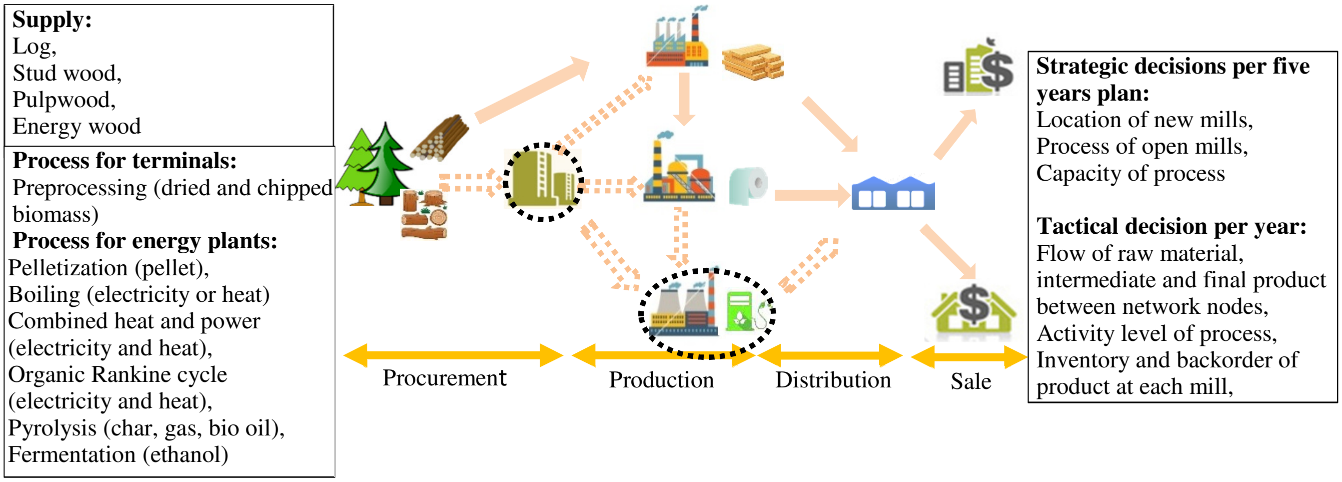

Figure 1. Forest biomass value chain design

interconnected networks, sectors, and products that clearly characterize its divergence.

Study about entire forest supply chain and its subsectors including solid wood and pulp and paper has attracted lots of attention in strategic, tactical and operational level of supply chain designing. D'Amours et al., (2008) demonstrated an overall view of conventional Canadian forest supply chain from harvest areas to the market. In their study, debarked trees called stems are transported to sawmills. Designing logistic network for lumber industry has been studied by Vila et al., (2006). Figure 2 depicted this subsector. As shown in the figure, produced chips in sawmills are transported to pulp and paper mills. High proficiency of this subsectors attracts a lots of research attention on the strategic and tactical level of supply chain designing [Martel et al., (2005), Carlsson et al., (2009), Weigel et al., (2010) and

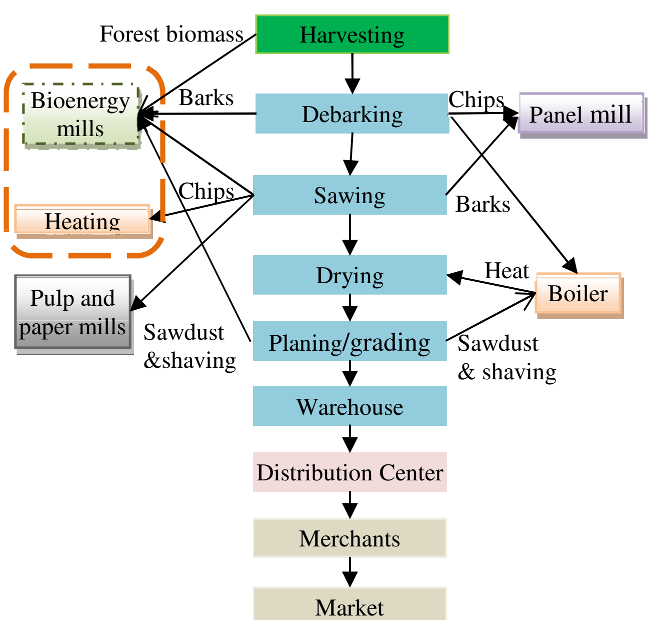

Figure 2. Wood lumber supply chain (Philpott and Everett, (2001))

Lumber and pulp and paper industries not only have efficacious in forest supply chain and Canada economy, but also could contribute in Canada's transformation from forest supply chain to forest biomass value chain. Indeed, their potential capacity and technologies to adapt to market fluctuation either by closing facilities or by modernizing their production technology made them very important to consider.

Furthermore, conversion of forest biomass has many advantages over Forestall, economic, and environmental areas. Protecting against firewood hazard, decrease dependency on crude oil, usage of local and regional renewable energies, the creation of many jobs and decline in carbon dioxide emission are some examples to imply its merit [Ragauskas et al., (2006), Hall and Scrase, (1998), Ahtikoski et al., (2008)]. Moreover regarding to Canadian forest industry survey in February 2011, the global market of bio-products creates opportunities of $200 billion [Natural Resource of Canada, (2013)]. The report states "that is no short-term consumer trend, but part of a "bio-revolution" that will change the future of forest resource use around the world".

Despite the aforementioned advantages, there are different challenges in designing biomass value chain. Convolution of its value chain as a part of complex forest supply chain could be declared as its most difficult challenge. Moreover, not homogenous geographic distribution of biomass, their different quality, and high transportation cost of balky biomass increased its barriers to expansion [Shabani et al., (2013)].

Designing a biomass value chain using optimization techniques is the best method to manage the proficiency of bioenergy markets. Several studies have used optimization techniques to address the biomass value chain network design problem in deterministic condition. Eriksson and Björheden, (1989) developed one of the first optimization models to manage forest-fuel suppliers. Since, several decision support systems for forest fuel has been developed in Europe [Gunnarsson et al., (2004), Frombo et al., (2009), Rentizelas et al., (2009) and Flisberg et al., (2012)]. It is worth to mention that in some of these studies, Flisberg et al., (2012) for instance, shows in their large case study a large saving with using forest fuels. However the earlier studies considered biomass value chain as standalone facilities with potential biomass supply resource and product market are

Ekşioğlu et al., (2009) and Parker et al., (2010). They considered both strategic and tactical decisions in their proposed design.

In the forest industry, Cambero et al., (2014) developed a strategic decision model for forest biomass value chain in order to support the merit of forest residues compare to the other alternatives for producing bioenergy and biofuels. Likewise, Feng et al., (2010) clarified the potentiality of the forest biomass value chain, as an integrated value chain. They considered a single organization owned several existing mills that wanted to make an investment in one or several biorefinery plants to be installed either within facilities or at the alternative greenfield sites. Moreover, Dansereau et al., (2012) considered a pulp and paper which has facilities for biorefinery products. Their objective was mitigating the risk of market volatility and designing a robust supply chain.

Nevertheless of comprehensiveness of aforementioned studies, uncertainty of biomass value chain in the new markets, new advanced materials, and associated technologies is conspicuous. Hence, In order to reduce risk of investment, designing a robust biomass value chain considering uncertainties is vital. However the complexity of uncertainty consideration in biomass value chain attracts less attention rather than deterministic problem. Kim et al., (2011b) considered uncertainty by performing sensitively analysis. They developed a general optimization model to select biomass supply locations, candidate sites and capacities for biofuel plants and the logistics of forest biomass. Meanwhile they did sensitive analyzes in order to investigate the most important parameters on the overall economics. They extend their work using stochastic optimization to tackle demand uncertainty of biofuels in biomass value chain [Kim et al., (2011a)]. Few other studies in tactical level of designing biomass value chain considering uncertainty especially on demand of biofuel have been developed [Svensson et al., (2011), Chen and Fan, (2012) and Tay et al., (2013)]. Svensson and Berntsson, (2011), For instance, investigated the development of pulp and paper mills process to produce biofuels considering uncertain energy market. forest biomass value chain under uncertainty in tactical level has been studied by Shabani et al., (2014). Uncertainty in designing biofuel supply chain has been reviewed by Awudu and Zhang, (2012). Finally, readers are referred to Shabani et al., (2013) for a comprehensive survey over forest biomass value chain optimization models in deterministic and stochastic contexts.

Most of above mentioned studies have focused on one particular bio-product including bioenergy, biofuel or other bioproducts, while lack of a studies which select different processes in order to produce different products from forest biomass is clearly evident. Moreover, uncertainty consideration makes the problem much more challenging. Indeed, design of forest biomass value chain for a real case study considering uncertainty is a real challenge but necessary one that is investigated in this study. The real case study is provided by FPInnovations and industrial partners.

The structure of the paper is as follows: in section 2 the problem description is provided. The proposed mathematical model is presented in section 3. Proposed methodology and some preliminary results are described in section 4. Finally, conclusion is given in section 5.

2 PROBLEM STATEMENT

Designing a sustainable and integrated forest biomass value chain considering uncertainty is vital to the transformation of the Canadian forest industry. This research project aims to propose an approach to address this challenging problem and support this transformation. Both inputs and outputs of our problem are well defined in Figure 1. The outputs could be integrated into a decision support system for much better and accurate strategic and tactical decisions for a robust and sustainable forest biomass value chain.

To design such sustainable value chain, one need to consider simultaneously different decision levels such as strategic, tactical and operational. Therefore, three main segments should be considered for this value chain. Firstly, strategic decisions comprise locating bioenergy or biofuel plants and terminals and assigning processes to them. Second, tactical decisions include flows of wood, biomass, final products, inventory and backorder within value chain. Lastly, all strategic and tactical decisions need to consider uncertainties.

2.1 How to deal with uncertainty

Designing forest supply chain in strategic level has been considered in Gunn, (2007). Now, the most daunting part of designing forest biomass value chain is existence of uncertainty on its supply, process, and market. Dealing with these uncertainties is not a new concept. Several approaches such as political decisions, forecasting uncertainties, selection of one network design among all possible ones, partnership and collaboration are common practices to tackle uncertainties in the industrial context. Nevertheless of simple appearance of conventional approaches, they have their own difficulties in practice. However, direct consideration of uncertainty will certainly lead to a more robust and sustainable value chain network. In this sense, stochastic programming (SP) and robust optimization (RO) are well-known optimization methods to deal with uncertainty.

Each of the aforementioned stochastic approaches are applicable in a variety of situations. Stochastic optimization aims to optimize the expected performance of network over a range of possible scenarios for the random parameters. In other words, we can expect that the system would behave optimally in the mean sense if the stochastic programming model solution was implemented. However, the system might perform poorly at a particular realization of scenarios, such as the worst-case scenario. Hence, robust optimization has been introduced to not only assure feasibility of our solution even for worst-case scenario but also ensures the solution less viability compare to stochastic optimization solution.

In this study, stochastic programming approach is used for our proposed model. In terms of stochastic solution, there exists an assumption that probability of uncertain parameters is known; hence, the expected performance value will be calculated based on the probability of uncertainties. Although SP often encounters two practical difficulties in calculation of expected value: firstly considering great number of scenarios poses high difficulties to calculate expect value, and next even if the numbers of scenario can be decreased, optimizing expect value is still a severe problem. The methods such as Sample Average Approximation method and scenario planning have been employed to solve the first challenge. Likewise, several design models such as two-stage stochastic optimization have been proposed to handle the second challenge. We employ scenario planning and two-stage optimization to tackle SP's difficulties.

2.1.1 Scenario Planning

In order to reduce the number of scenarios, scenario planning is applied. This method restricts our scenarios to specified ones which are the most possible future happenings. For our proposed problem, demand and price of biofuels as our uncertain parameters are assorted to three levels of low, moderate and high (Figure 3). Each possible interaction between uncertain parameters is considered as a scenario.

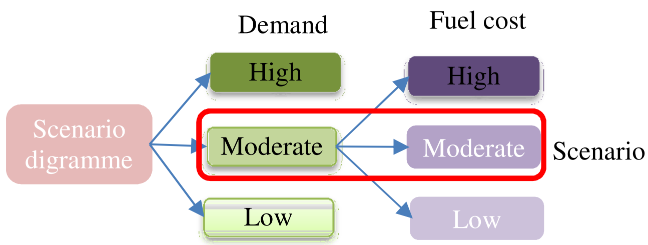

Figure 3. Scenario planning

2.1.2 Two-Stage Stochastic Programming

In order to decrease complexity of stochastic optimization dependent on uncertain parameters, two-stage stochastic optimization divided the set of decision variables in two groups [Birge and Louveaux, (2011)]:

Firstly, a number of decisions have to be taken before uncertain parameters are revealed. All these decisions are called first-stage decisions and the period when these decisions are taken is called the first stage. Secondly, a number of decisions can be taken after uncertain parameters are revealed. They are called second-stage decisions. The corresponding period is called the second stage. If first-stage decisions represented by the vector y, second-stage decisions represented by the vector x or $x(\xi(\omega))$ or $x(\xi(\omega), y)$ where $\xi(\omega)$ is vector of uncertainty.

3 The Mathematical Model

We consider the entire value chain network from suppliers to customers in Figure 4 as a network graph $G(N,A)$ where N, and A are set of nodes, and network flows respectively. N is the union of several sets of nodes consisting of H as set of harvest areas, M^{saw}, M^{pulp} as set of manufacturing plants including saw mills and pulp and paper mills, L^T and L^E as set of potential location for terminals and biofuel plants, and C as set of costumers. Terminals and biofuel plants candidates should be selected for entire time horizon. Likewise, set of assignable processes for each manufacturing plant should be selected. Moreover, flow of materials and their inventory and backorder at each mill should be determined for each time period depend on uncertainty on the transportation cost and could assort to process productivity, cycle time, and yield uncertainty. However, here, we only consider process yield as an uncertain parameter. The objective function is maximizing total profit value of biomass value chain.

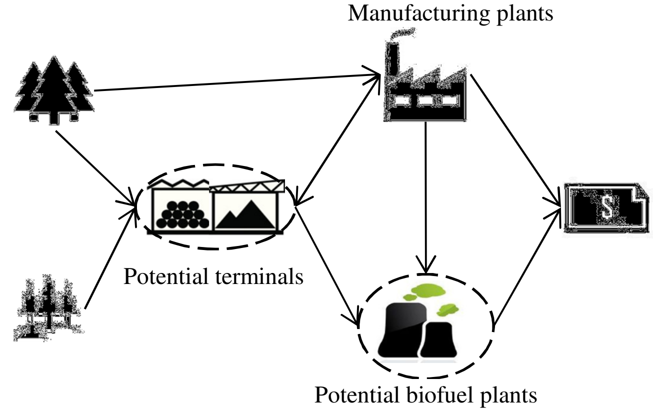

Figure 4. Forest biomass network graph

In general view, model characteristic is presented in Figure 5.

To formulate the model, the following indexes, sets, parameters, and decision variables are defined:

Indices and Sets:

S	set of scenarios
T	set of time periods
P^{RM}	set of raw materials including logs, forest residues and chips
P^{Fin}	set of final products including lumbers, pulp and papers and biofuel
P	set of product type $P = P^{RM} \cup P^{Fin}$
H	set of harvest areas
M^{saw}	set of saw mills
M^{pulp}	set of pulp mills
L^T	set of potential terminal locations
L^E	set of potential energy plant locations
C	set of costumers
N	set of network nodes $N = H \cup M^{saw} \cup M^{pulp} \cup L^T \cup L^E \cup C$
I_{ip}	subset of network nodes for start of incoming flows of product $p \in P$ to node $i \in N$ ($I_{ip} \subset N$)
J_{ip}	subset of network nodes for destination of outgoing flow of product $p \in P$ from node $i \in N$ ($J_{ip} \subset N$)
R_i	set of candidate process for node $i \in M^{saw} \cup L^T \cup L^E$
K_i	set of available capacity for node $i \in M^{saw} \cup L^T \cup L^E$
K_i^R	set of process capacity at node $i \in M^{saw} \cup L^T \cup L^E$

Parameters:

b	investment budget
f_i^E	fixed cost to open energy plant $i \in L^E$
f_i^T	fixed cost to open terminal $i \in L^T$
f_{ir}^R	fixed cost to use process $r \in R_i$ at node

$i \in M^{saw} \bigcup L^T \bigcup L^E$

pr_s Probability of occurrence scenario $s \in S$

$d^{\min}_{pist}$ minimum demand of product $p \in P$ at node $i \in N$ for Scenario $s \in S$ in time period $t \in T$

$d^{\max}_{pist}$ maximum demand of product $p \in P$ at node $i \in N$ for Scenario $s \in S$ in time period $t \in T$

v_{pt} unit selling value of product $p \in P$ in time period $t \in T$

c^{pur}_{pt} unit purchasing cost of product $p \in P$ in time period $t \in T$

c^{l}_{pit} unit inventory cost of product $p \in P$ at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ in time period $t \in T$

c^{b}_{pit} unit backorder cost of product $p \in P$ at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ in time period $t \in T$

c^{Trans}_{pijst} unit transportation cost for product $p \in P$ between nodes $i, j \in N$ for scenario $s \in S$ in time period $t \in T$

c^{R}_{ir} unit processing cost of process $r \in R_i$ at node $i \in M^{saw} \bigcup L^T \bigcup L^E$

a^{IN}_{pir} unit amount of input product $p \in P$ used at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ in process $r \in R_i$ per one time of using process

a^{OUT}_{pir} unit amount of output product $p \in P$ used at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ in process $r \in R_i$ per one time of using process

o_{pirt} resource used to produce one unit of product $p \in P$ by process $r \in R_i$ at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ in time period $t \in T$

k^{R}_{ir} capacity of process $r \in R_i$ at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ ($k^{R}_{ri} \in K^{R}_{i}$)

k_i capacity of node $i \in M^{saw} \bigcup L^T \bigcup L^E$ ($k_i \in K_{LT}$)

Decision variables:

y^{E}_{ik} 1 if energy plant $i \in L^E$ with capacity $k \in K_{L^E}$ is open, and 0 otherwise

y^{T}_{ik} 1 if terminal $i \in L^T$ with capacity $k \in K_{L^T}$ is open, and 0 otherwise

y^{R}_{ir} 1 if process $r \in R_i$ is used at node $i \in M^{saw} \bigcup L^T \bigcup L^E$, and 0 otherwise

l_{pist} inventory of product $p \in P$ at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ for scenario $s \in S$ in time period $t \in T$

b_{pist} backorder of product $p \in P$ at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ for scenario $s \in S$ in time period $t \in T$

x^{f}_{pijst} flow of product $p \in P$ between nodes $i \in I_{ip}$ and $j \in J_{ip}$ for scenario $s \in S$ in time period $t \in T$

x^{R}_{pirst} The activity level of process $r \in R_i$ for product $p \in P$ at node $i \in M^{saw} \bigcup L^T \bigcup L^E$ for scenario $s \in S$ in time period $t \in T$ (the number of usage of process)

We formulate the design of forest biomass value chain problem under uncertainty as a two-stage stochastic program where strategic decisions (first stage decisions) are made in first stage, followed by tactical decisions (second stage decisions)such as flows of material, inventory and backorders in the second stage. The mathematical formulation is as follow:

$$Max\, Z: \sum_{s \in S} pr_s Q(y,s) - \sum_{i \in L^E} \sum_{k \in K_i} f^{E}_{ik} y^{E}_{ik} - \sum_{i \in L^T} \sum_{k \in K_i} f^{T}_{ik} y^{T}_{ik} - \sum_{i \in M^{saw} \bigcup L^T \bigcup L^E} \sum_{r \in R_i} f^{R}_{ir} y^{R}_{ir} \quad (1)$$

s.t:

$$\sum_{i \in L^E} \sum_{k \in K_i} f^{E}_{ik} y^{E}_{ik} + \sum_{i \in L^T} \sum_{k \in K_i} f^{T}_{ik} y^{T}_{ik} + \sum_{i \in M^{saw} \bigcup L^T \bigcup L^E} \sum_{r \in R_i} f^{R}_{ir} y^{R}_{ir} \le b \quad (2)$$

$$y^{R}_{ir} \le \sum_{k \in K_i} y^{T}_{ik} \qquad \forall i \in L^T, r \in R_i \quad (3)$$

$$y^{R}_{ir} \le \sum_{k \in K_i} y^{E}_{ik} \qquad \forall i \in L^E, r \in R_i \quad (4)$$

$$\sum_{k \in K_{L^T}} y^{T}_{ik} \le 1 \qquad \forall i \in L^T \quad (5)$$

$$\sum_{k \in K_{L^E}} y^{T}_{ik} \le 1 \qquad \forall i \in L^E \quad (6)$$

$$y^{T}_{ik} = \{0,1\} \qquad \forall i \in L^T, k \in K_i \quad (7)$$

$$y^{E}_{ik} = \{0,1\} \qquad \forall i \in L^E, k \in K_i \quad (8)$$

$$y^{R}_{ir} = \{0,1\} \qquad \forall i \in M^{saw} \bigcup L^T \bigcup L^E, r \in R_i \quad (9)$$

Where $Q(y,s)$ is:

$$Q(y,s) = \mathrm{M}ax \sum_{p \in P} \sum_{i \in I_{ip}} \sum_{j \in J_{ip}} \sum_{s \in S} \sum_{t \in T} v_{pt} x^{f}_{pijst} - \sum_{p \in P} \sum_{i \in I_{ip}} \sum_{j \in J_{ip}} \sum_{s \in S} \sum_{t \in T} (c^{pur}_{pt} + c^{Trans}_{pijst}) x^{f}_{pijst} - \sum_{p \in P} \sum_{i \in M^{saw} \bigcup L^T \bigcup L^E} \sum_{s \in S} \sum_{t \in T} c^{l}_{pit} l_{pist} - \sum_{p \in P} \sum_{i \in M^{saw} \bigcup L^T \bigcup L^E} \sum_{s \in S} \sum_{t \in T} c^{b}_{pit} b_{pist} - \sum_{p \in P} \sum_{i \in M^{saw} \bigcup L^T \bigcup L^E} \sum_{r \in R_i} \sum_{s \in S} \sum_{t \in T} c^{R}_{r} x^{R}_{pirst} \quad (10)$$

S.t:

$$\sum_{j \in J_i} x^{f}_{pijst} \le k^{H}_{pi} \qquad \forall p \in P, i \in H, s \in S, t \in T \quad (11)$$

$$x^{f}_{pijst} \le d^{\max}_{pist} \qquad \forall p \in P, i \in L^E, j \in J_{ip}, s \in S, t \in T \quad (12)$$

$$x^{f}_{pijst} \ge d^{\min}_{pist} \qquad \forall p \in P, i \in L^E, j \in J_{ip}, s \in S, t \in T \quad (13)$$

$$l_{pist-1} + \sum_{j \in I_{ip}} x^f_{pjist} + \sum_{r \in R_i} a^{out}_{rp} x^R_{pirst} - \sum_{r \in R_i} a^{IN}_{rp} x^R_{pirst} - l_{pist} = 0 \qquad \forall p \in P^{RM}, i \in M^{saw} \cup L^T \cup L^E, s \in S, t \in \{1\} \quad (14)$$

$$l_{pist-1} + \sum_{j \in I_{ip}} x^f_{pjist} + \sum_{r \in R_i} a^{out}_{rp} x^R_{pirst} - \sum_{r \in R_i} a^{IN}_{rp} x^R_{pirst} - \sum_{j \in J_{ip}} x^f_{pijst} - l_{pist} + b_{pist} = 0 \qquad \forall p \in P^{Fin}, i \in M^{saw} \cup L^T \cup L^E, s \in S, t \in \{2,..,T\} \quad (15)$$

$$\sum_{p \in P} l_{pist} \le \sum_{k \in K_i} k_i y^T_{ik} \qquad \forall i \in L^T, s \in S, t \in T \quad (16)$$

$$\sum_{p \in P} l_{pist} \le \sum_{k \in K_i} k_i y^E_{ik} \qquad \forall i \in L^E, s \in S, t \in T \quad (17)$$

$$\sum_{p \in P} l_{pist} \le k_i \qquad \forall i \in M^{saw}, s \in S, t \in T \quad (18)$$

$$\sum_{p \in P} o_{pirt} x^R_{pirst} \le k^R_{ri} y^R_{ri} \qquad \forall i \in M^{saw} \cup L^T \cup L^E, r \in R_i, s \in S, t \in T \quad (19)$$

$$\sum_{p \in P} \sum_{j \in J_{ip}} x_{pijst} \le \sum_{k \in K_i} k_i y^T_{ik} \qquad \forall i \in L^T, s \in S, t \in T \quad (20)$$

$$\sum_{p \in P} \sum_{j \in J_{ip}} x_{pijst} \le \sum_{k \in K_i} k_i y^E_{ik} \qquad \forall i \in L^E, s \in S, t \in T \quad (21)$$

$$x^f_{pijst}, x^R_{prist} \ge 0 \qquad \forall i \in I_{ip}, j \in J_{ip}, r \in R_i, s \in S, t \in T \quad (22)$$

The model is a two stage stochastic programming model with an objective function that aims maximizing total profit. Constraint (2) considers the limited available budget, locates energy plants and terminals and allocates processes to sawmills, terminals, and biofuel plants. Constraints (3) and (4) assure selecting a process for the open terminals and biofuel plants. The capacity of these open terminals and biofuel plants is selected in constraints (5) and (6), respectively. In the second stage, the objective function is maximization of profit considering sale revenues and purchasing, transportation, inventory, backorder and processing costs. Capacity limitation of all of product in harvest areas is considered in constraint (11). Constraints (12) and (13) state that demand of each biofuel at energy plants varies between minimum and maximum of uncertain demand, respectively. The constraints (14) and (15) are balance constraints at saw mills, terminals and energy plants during time period. Moreover, the capacity constraint for inventory at these nodes is considered in constraints (16), (17) and (18), respectively. The resource capacity constraint for each process at sawmills, terminals and energy plants is considered in constraint (19). Finally, constrains (20) and (21) allows flows from or to terminals and biofuel plants, if they are opened in the first-stage model.

4 PROPOSED METHODOLOGY

Although we modeled the biomass value chain design problem as a two-stage stochastic programming model, the model is too large to solve and its solution time is long for realistic and large scale cases. Moreover the exponential increase of the size of our model based on the number of facilities and products makes it really hard to solve for large scale problems. For instance, for a case study with two harvest areas, one sawmill, three potential location for terminals, one potential location for biofuel plant and nine scenarios, the model has 5476 decision variables, however by adding just one biofuel plant the number of variables increase to 6458. Hence, in order to divide problem to smaller models with shorter solution time, L-shaped method could be a useful methodology (Tang and Zhao, (2003)). Moreover, it has been proofed that the L-shaped method converges to an optimal solution [Birge and Louveaux, (2011)].

L-shaped method divides the main model to a master problem corresponding strategic decisions for value chain overall time horizon and several sub problems corresponding tactical decisions for each scenario. The expected value of the dual variables of sub problems' objective function is responsible for linking master and sub problems. General idea is smoothly converging to optimal solution by adding feasibility or optimality cut to the master problem.

The method commences with solving master problem. In next iteration, considering first stage decision variables, sub problems should find the optimal solution for each scenario. However two different cases may happen; either sub problems have feasible solutions or at least one of them encounters with infeasibility. In the first case, the expected value of dual of sub problems' objective function will add as optimality cut to the master problem. However in the second case, the infeasibility array multiply by dual of sub problems' objective function will add as a feasibility cut to the master problems in order to prevent this infeasibility in the next iterations. Afterward, the process will start again till first-stage solution doesn't change. The algorithm for a simple model is described as following:

Step 0- Initializing:

Set $\theta_0 = -\infty$

Step 1- solving master problem Z:

$Min\, Z = y + \theta$

subject to:

$\theta \ge \theta_0$

Step 2- solving sub problem per scenarios:

$Min\, F(s) = C^T_s\, x_s$

$st.$

$Con1: Ax_s - by \le h_s$

$Con2: Tx_s \le h_s$

If sub problems are feasible, go to step 3, else go to step 4.

Step 3- adding optimality cut:

Calculate

$\theta_0 = P_s \times Con1.dual \times -(Ax_s - by) + P_s \times Con2.dual \times (h_s - Tx_s)$

If $\theta > \theta_0$ then go to step 5, else optimality cut of $\theta > P_s \times Con1.dual \times -(Ax_s - by) + P_s \times Con2.dual \times (h_s - Tx_s)$ considering x_s known, should add to master problem and go to step 1.

Step 4-adding feasibility cut:

Since in our proposed model we have backorder decision variables, we may not face with non-feasibility in our sub problems. Go to step 1.

Step 5- end of algorithm:

The solution which is found is optimal for master and sub problems.

5 Preliminary Result of Algorithm

Figure 5 displayed the considered case study. The green blocks in the picture are forest harvest areas which have 2 km × 2 km size. Newfoundland has 5888 number of such blocks and at each block, different woods and biomass are harvesting. Five existed mills are operating and their final products are mainly conventional forest product including, lumber and pulp and paper. Since the island has a high availability of forest biomass, this case is well suitable for our problem. In our generic model three potential location for new energy plants with seven possible processes is considered. Moreover, the large distance between scattered forest blocks and existing mills, lead us to consider adding new terminals (merchandising yards). Two potential terminal locations with opportunity of set up preprocessing are taken into account. Each supposed process may be installed in different capacity. These assumptions make the mathematical model extremely hard to solve. Solving such model with the real case study is underway but not yet finished. Data availability and accuracy are additional challenges in this type of approaches as the models are data-intensive. Our close collaboration with FPInnovations and industrial partners helps us to overcome these obstacles. New technologies (Lidar, sensors, etc.) show promise in reducing these uncertainties but the tradeoff between cost and accuracy will remain. Data collection and validation are underway. However in order to testify our model we used a small case study inspired form the real case study.

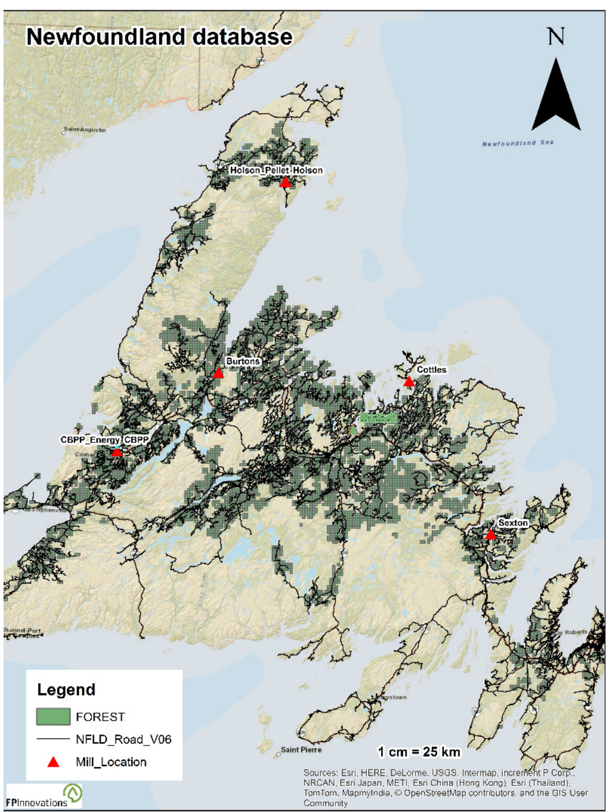

Figure 5. Real case study view

The small case (Figure 6) comprises of two harvest areas, one saw mill, one market, three potential locations for terminals and one for biofuel plants, have considered to validates our proposed model.

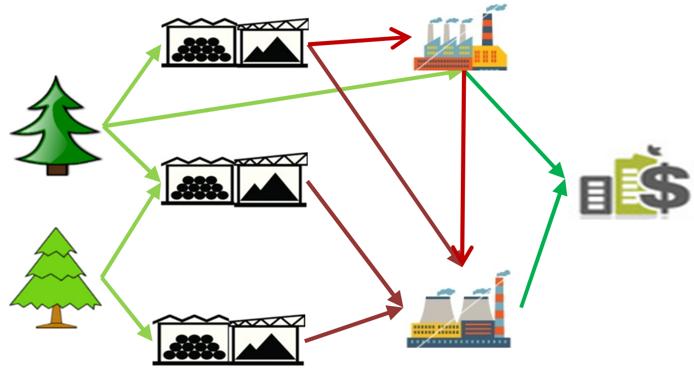

Figure 6. Sample case

Moreover, information about the raw material, intermediate and final product and candidate process at manufacturing plants are presented in table 1 and 2 respectively.

Table 1. product definition

name	definition
P1	Logs
P2	Low quality logs
P3	Chips, forest residues
P4	Preprocessed pellet
P5	Lumber
P6	Pellet

Table2. candidate process at each value added mills

	sawmill	terminal	Biofuel plant
Input	P1	P2, P3	P4
Output	P3,P4,P5	P4	P6
Process	R1:P1--> (P3,P4,P5)	R2:P2-->P3 R3:P3-->P4	R4:P4-->P6

The model has been coded in AMPL version 2014.12.3.1 in a standard laptop computer equipped with core i7 processor and 8 Gig Bite Ram, under windows 7 operating system. The solution time is less than a second.

The optimal solution depicted in Figure 7 is found after five iterations of L-shaped method. The strategic decisions for this value chain is opening one terminal and one biofuel plant using the chipping (R3) and preparation (R2) processes at opened terminal and sawing (R1) process at sawmill and pelletization (R4) process at opened biofuel plants.

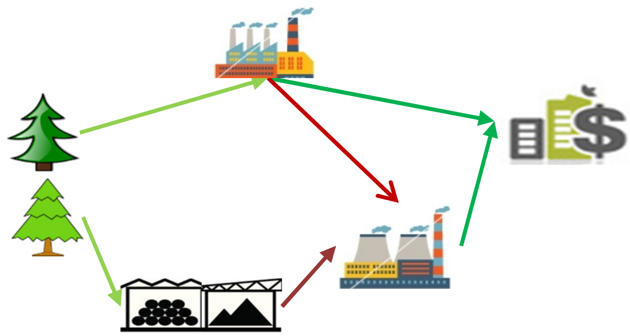

Figure 7. Optimal solution for proposed sample case

In order to evaluate the efficiency of our stochastic optimization algorithm, we compared our stochastic solution with each scenario. In terms of objective values Table 3 illustrates the efficiency of stochastic solution. Moreover, in terms of strategic decisions, none of nine scenarios did not do chipping process at terminals, however the stochastic solution did it. This process reduces transportation cost of bulky chips and in this way reduce costs.

Table 3. objective value of each scenario if it happen in future

Scenarios	Objective value ($)
S1	344,331
S2	358,346
S3	367,196
S4	371,549
S5	386,917
S6	393,704
S7	387,880
S8	394,536
S9	393,704
Average	377,573

On the side, the objective value for our proposed methodology considering all nine scenarios with their probability is 348,561$. Hence, there is a gap of 29,102$ between the average value and our proposed approach, which is equivalent to approximately to 8%. This gap between the two approaches could be interpreted as the value of stochastic solution.

6 Conclusion

Energy generation from forest biomass could assure a smooth transformation for the Canadian forest industry. However, this transformation requires decisions supports systems for better network design decisions under all possible futures with an emphasis on the logistic costs and market of forest biomass value chain. We study value chain design defining several scenarios on aforementioned future happenings. Since the results for the real case study are underway, a small case study has been used to validate the value of using stochastic optimization in such problem. 8% decrease in objective function value compare to deterministic solution, showed the preference of our developed model. Such a high value of stochastic optimization could create a great motivation for researchers to confront difficulty of uncertainty consideration. This may bring new efficient methods for stochastic problems. Moreover from socio-economic perspectives, construction of these new mills not only increases the province's revenues, but also creates more jobs opportunities for local communities.

For further research, forest biomass value chain could be extended using different technologies in biofuel plants considering uncertainty on their yields. Moreover different forest biomass qualities which affect technology yield could be considered. In terms of solution methods, robust optimization methods could be used for all proposed models in further researches. We will also study the performance on realistic design instances.

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