Canadian Journal of Forest Research
Revue canadienne de recherche forestière

Development of an economically sustainable and balanced tactical forest management plan: a case study in Québec

Journal:	<i>Canadian Journal of Forest Research</i>
Manuscript ID	cjfr-2017-0232.R1
Manuscript Type:	Article
Date Submitted by the Author:	18-Sep-2017
Complete List of Authors:	Mobtaker, Azadeh; Ecole de technologie superieure, Automated manufacturing engineering, 1100, rue notre Dame Ouest Ouhimmou, Mustapha; Ecole de technologie superieure, automated manufacturing engineering Rönnqvist, Mikael; Université Laval, Département de génie mécanique Paquet, Marc; Ecole de technologie superieure, Automated manufacturing engineering
Keyword:	Tactical forest management planning, Mutli-objective optimization, Goal programming, Nadir theory, Sustainability
Is the invited manuscript for consideration in a Special Issue? :	N/A

SCHOLARONE™
Manuscripts

1 **Development of an economically sustainable and balanced tactical forest**
2 **management plan: a case study in Québec**

3
4 Azadeh Mobtaker, Mustapha Ouhimmou, Marc Paquet
5 École de technologie supérieure
6 1100, rue Notre-Dame Ouest, Montréal (QC) – Canada
7 Emails: azadeh.mobtaker.1@ens.etsmtl.ca;
8 mustapha.ouhimmou@etsmtl.ca;
9 marc.Paquet@etsmtl.ca

10
11 Mikael Rönnqvist
12 Université Laval
13 1065, av. de la Médecine, Québec (QC) – Canada
14 Email: mikael.ronnqvist@gmc.ulaval.ca

Development of an economically sustainable and balanced tactical forest management plan: a case study in Québec

Abstract:

In Canada, most of the forests are publicly owned and forest products companies depend on timber licenses issued by the provincial governments for their wood supplies. According to the Sustainable Forest Development Act effective in the province of Québec since April 2013, the government is responsible for harvest area selection and timber allocation to companies. This is a complex tactical planning decision, with important impacts on downstream economic activities. Moreover, in order to avoid high-grading of forest resources and to determine a sustainable tactical plan which ensures a stable level of availability, quality and cost of supply over several years, it is necessary to simultaneously take these criteria into consideration during the planning process. We propose a mixed-integer nonlinear goal-programming formulation while employing Nadir theory as a reliable scaling technique to model this multi-objective planning problem. The model is solved by a linearization approach for a real case in the province of Québec. The proposed solution method enables us to obtain good-quality solutions for relatively large cases. Results show the proposed model outperforms conventional cost-minimization planning strategy by ensuring a more balanced use of wood supply and costs for all stakeholders over a longer period.

Keywords:

Tactical forest management planning, Mutli-objective optimization, Goal programming, Nadir theory, Sustainability

37 1. Introduction and literature review

38 In Canada as a major forested country, forest resources provide significant
39 environmental, social and economic value, and in order to exploit this value the forest
40 products industry is organized in a complex industrial system known as a value chain,
41 starting from the forest up to markets (Audy *et al.*, 2016). The five main value chains of a
42 forest-based value creation network are Forest, Lumber, panel, and engineered wood
43 products, Pulp and Paper, Biorefinery and Bioenergy. In this study we focus solely on the
44 forest value chain, which mainly involves forest management, harvesting and log
45 transportation activities, while other value chains produce different types of final
46 products to be sold in various markets. Fleischmann *et al.* (2008) structured a two-
47 dimensional matrix for categorization of supply chain planning problems from two
48 perspectives: the main processes along the supply chain (i.e., procurement, production,
49 distribution and sales) and the planning horizon (i.e., strategic, tactical and operational).
50 Different stages of planning based on the time-perspective planning horizon could
51 involve substantially different planning tasks. For instance, strategic forest planning
52 normally covers a horizon of a few decades to hundreds of years and may involve
53 decisions about the design and structure of forest value chain network, development of
54 forest management strategies/policies, silviculture treatments, selection of conservation
55 areas, etc. Tactical planning often addresses a full seasonal cycle (from 1 to 5 years) and
56 decisions about how to treat standing timber and allocate them to specific mills to fulfill
57 certain demands are made at this level. Finally, at the operational level, planners deal
58 with day-to-day issues of harvesting and transportation; see e.g., the review by D'Amours
59 *et al.* (2011).

60 Exploiting forest resources through more integrated and sustainable planning has proved
61 invaluable especially for countries such as Canada with over 350 million hectares of
62 forest land representing almost 9% of the world's forests. Most of Canada's forests are
63 publicly owned and provincial governments are responsible for stewardship of Crown
64 land. For example, in the province of Québec, forests account for 2% of the world's
65 forests and the forest products industry including over 400 wood processing plants is one
66 of the main economic drivers of the province, generating about 80,000 jobs directly
67 related to the forestry sector (Government of Québec, 2017). In recent years the Canadian
68 forest products industry has encountered critical challenges like substantial decrease in
69 newsprint paper demand and in softwood lumber exportation to the United States to name
70 a few, which has forced policy makers to seek new forest management strategies and
71 policies. In March 2010, Québec's National Assembly unanimously agreed on the
72 Sustainable Forest Development Act (Chapter A-18.1). The new Act presents some
73 changes in Québec's forest stewardship system. It gives the Ministry of Forests, Fauna
74 and Parks (MFFP) responsibility for preparing and implementing integrated forest
75 development plans, so MFFP will have the power to take local needs and goals into
76 account (Légis Québec, 2016). Particularly, the Québec Government has become
77 responsible for harvest planning and wood allocation to wood-processing mills since
78 April 2013. So, in order to fully benefit from the new regime, the MFFP is in need of an
79 integrated planning system for the development of a tactical forest management plan that
80 ensures a balanced consumption of the woody resources over a five-year planning
81 horizon in terms of, for instance, cost, stems' average size and average volume per
82 hectare. Balancing these criteria throughout the planning horizon would allow the MFFP

to ensure that public forest is capable of supplying the wood-processing mills and avoid wood shortages in specific territories over longer time.

Researchers particularly in countries with vast forestlands like Chile, Sweden and Canada have been studying the tactical forest value chain planning problem for years. Most of the relevant decision support systems (DSS) developed for these types of planning problems found in the literature aim to support forest harvesting and/or raw material transportation-related decisions, but solely from a single-objective optimization (revenue maximization and/or cost minimization) perspective. A few studies also include the production process.

In Chile for instance, Epstein *et al.* (1999) developed a mixed-integer programming (MIP) DSS called OPTIMED, for tactical forest planning (harvesting and road building). OPTIMED uses binary variables to represent whether or not to build or upgrade roads. In order to solve the developed MIP formulation, the authors proposed to include valid inequalities to strengthen the formulation and a heuristic rounding approach to generate feasible solutions. Troncoso *et al.* (2015) proposed an MIP model for a demand-driven integration of forest value chain of a Chilean forest company. Results show that the integrated approach could lead to up to 5% more net present value than the decoupled strategy.

For years Swedish forest transportation planning was done manually and decentralized to districts. Forest planners recognized great potential for improved efficiency and cost saving in the supply chain through identifying a better match between the supply and demand points, better use of back haulage tours and better coordination among districts and/or companies. Forsberg *et al.* (2005) presented a decision aid tool FlowOpt that

supports both tactical and strategic transportation and harvesting planning for the Swedish forest industry. It determines mills' allocation of timber, back hauling possibilities for reducing empty driving, location of train terminals and mechanisms for cooperation among companies. Later on, road opening/upgrading decisions with consideration of variations in road accessibility conditions due to the weather conditions were incorporated into another model developed by Karlsson *et al.* (2006) named RoadOpt which plans demand-driven annual harvesting and transportation. Carlgren *et al.* (2006) also developed an MIP model for harvesting and transportation planning, while alternative strategies for sorting the logs in the forest and the possibility of back-haulage tours have been analyzed. The authors solved the model using a combination of column generation and branch-and-bound techniques.

In Canada, Beaudoin *et al.* (2007) presented an MIP model to support the tactical wood procurement decisions in a demand-driven multi-facility environment. Harvest scheduling and wood transportation decisions were modeled with the goal of maximizing a firm's profit while satisfying demand for end products, wood chips as well as demand for logs from other companies. As opposed to cases with disintegrated forest value chains where decisions about optimized use of harvesting resources (e.g. machineries and teams) are made separately from harvest scheduling decisions, the authors also included the cost associated with movement of machinery from one harvesting area to the next in their model. In another study by Ouhimmou *et al.* (2008) the production process of an integrated furniture assembly mill supply chain is subsumed into the tactical forest management planning problem. The authors formulated the multi-site and multi-period planning for procurement, sawing, drying, and transportation operations in an MIP

128 model. A heuristic algorithm based on time decomposition approach is used to solve the
129 model for large-sized examples. Bouchard *et al.* (2017) modeled the integrated strategic
130 and tactical forest products value chain. Testing the models for a large-scale instance
131 located in Canada showed that using the integrated approach could lead to up to 13%
132 profit gain.

133 Kangas *et al.* (2014) proposed a hierarchical optimization model combining top-down
134 and bottom-up approaches to determine the annual stand-level harvest schedules.
135 Duvemo *et al.* (2014) developed a simulation system to address the hierarchical tactical-
136 operational level forest planning. Stand databases of Swedish companies are used to
137 conduct cost-plus-loss analysis. Gautam *et al.* (2016) also proposed a simulation-
138 optimization system to model hierarchical forest management. Testing the model for a
139 Canadian case showed that between 2-3.7% increase in the profit could be obtained by
140 allowing silvicultural flexibility at the operational level.

141 To sum up, in the literature of tactical forest management, harvest planning and wood
142 allocation decisions have been addressed often accompanied by incorporation of one or
143 more of the following matters, e.g. road engineering, back-haulage tours, log sorting
144 strategies at the forest roadside, spatial considerations, etc. Diaz-Balteiro and Romero
145 (2008) have reported timber harvest planning as the first branch of forestry where the
146 multiple-criteria decision-making paradigm has been applied. However, almost all of the
147 few published articles in this category have explored the harvest planning problem at the
148 strategic level covering planning horizons of 25 to hundreds of years (e.g., Kao and
149 Brodie, 1979; Ducheyne *et al.* 2004; Diaz-Balteiro and Romero, 2003). At short-term
150 planning, Hotvedt *et al.* (1982) proposed a heuristic approach for weight setting for a

cardinal goal programming (GP) model of an operational harvest scheduling problem. In fact, GP has become a well-accepted approach for multi-objective planning problems in various forestry topics. For instance, Diaz-Balteiro and Romero (2003) developed several lexicographic GP models in order for efficient incorporation of carbon sequestration into a harvest scheduling problem over a planning horizon of 100 years. Another example in the category of forest biodiversity conservation, Lundström *et al.* (2011) also used GP to perform a reserve selection analysis in boreal forest in Sweden. The cost of preserving each plot as a reserve was analyzed by considering seventeen biodiversity measures. Lundström *et al.* (2014) extended their earlier model by using Analytic Hierarchical Process (AHP) to systematically determine the relative importance of considered biodiversity criteria.

At the tactical level, Kazana *et al.* (2003) developed an interactive decision support framework for the management of multiple use forests. The combined MINMAX approach is used to generate many forest management alternatives. Different criteria including timber production, dispersed recreation, water-based recreation and deer stalking for certain habitat types were taken into account. Johansen *et al.* (2017) studied the problem of efficient forest resource usage. They developed a strategically-tactically oriented mathematical business economic model that combines value chain optimization modeling with the regional macro-economic theory. All the studied criteria were presented in monetary values and Pareto curves were used to demonstrate the trade-off between value chain profit (industry focus) and value creations related to political and social impacts (based on revenues).

173 Laukkanen et al. (2005) addressed a multi-criteria tactical timber-harvest planning
174 focusing on the group decision making. The authors adopted a voting-based-theory
175 method to generate alternative plans that were evaluated with respect to the following
176 criteria: net harvesting income, effects on nature conservation values, effects on
177 recreational values, expectation of logging damage and favoring local contractors. Ezzati
178 et al. (2016) developed a spatial multi-criteria decision making tool to generate “sub-
179 optimal” solutions for harvest operations decisions in mountainous areas. The authors
180 employed analytical network structure method along with the weighted linear
181 combination function to model and solve the defined problem.

182 To the best of the authors’ knowledge, there are very few works addressing the tactical
183 level multiple-criteria forest planning problem and there is great room for further
184 research; and in that respect our contribution to the literature can be summarized as
185 follows. We simultaneously consider three specific criteria in order to propose an
186 efficient plan which ensures a stable level of cost, quality/size and availability of wood
187 supply to forest products companies over five years of planning. In addition, we have
188 made use of the idea of business and anticipation periods in the context of a rolling
189 horizon re-planning strategy in order to accommodate in our model the means to prevent
190 high-grading in the use of wood supply over the planning horizon as well as overcoming
191 the challenge of lack of demand information for the last four years of the considered
192 planning horizon. We have proposed a mathematical formulation for each of the
193 considered criteria and developed a solution methodology based on GP approach where
194 several mixed-integer nonlinear programming (MINLP) and MIP optimization models
195 are solved and analyzed. Additionally, in this work we take advantage of the Nadir theory

and Payoff Table method for the normalization of the formulated objective functions which are incommensurable and have values of different magnitude. Moreover, we have proposed a linearization approach enabling us to obtain good quality solutions for the proposed MINLP models (which are often very difficult to solve, even for small cases) in large instances within a reasonable time.

The structure of this paper is as follows: in Section 2 the research problem is described in detail. The solution approach and the proposed mathematical formulation are presented in Sections 3 and 4 respectively. Section 5 describes the developed Canadian case study. The discussion on the computational tests is presented in Section 6. This paper ends with conclusions and some future research avenues in Section 7.

2. Problem description

Consideration of multiple criteria in forest management planning has become a necessity rather than a special case (Rönnqvist *et al.*, 2015). In that regard, the current study addresses the problem of selection of harvesting areas and wood allocation to forest products companies over a five-year planning horizon from a multiple objective optimization standpoint. In particular, the goal is to select harvest areas and define the wood allocation for year one to fulfill the demand at mills while concurrently balancing three specific criteria over the whole planning horizon. The examined criteria are average unit purchasing and transportation cost, average volume per stem and average volume per hectare.

216 Rönqvist *et al.* (2015) describe the most recent research challenges and open questions
217 on application of operations research techniques in forestry. The defined problem in this
218 paper can relate to two of the open problems (OP) named in Rönqvist *et al.* (2015):

219 OP 32: How can we incorporate the preferences of the decision maker for the different
220 criteria into the multi-criteria model?

221 OP 33: How can we develop multi-criteria approaches that are rigorous in thoroughly
222 incorporating the decision maker's preferences, yet user friendly?

223 With respect to OP 32, we collect information on several objectives, include them into a
224 goal programming approach, make a correct scaling/normalization and finally we analyze
225 the impact/cost of these objectives; and in connection with OP 33, we formulated
226 multiple periods of the objectives by scaling mills' demand. Without this, it would be
227 difficult to examine the multiple objectives correctly.

228 Every year, the MFFP replenishes a register of harvest areas as new areas are surveyed.
229 Even though the MFFP aims to have enough harvest areas in the register to cover five
230 years of harvesting, often the pool has fewer harvest areas than needed for five years.
231 Additionally, each year the demand situation and road network accessibility may change.
232 That is why decision makers (DM) adopt a rolling horizon re-planning strategy and need
233 to run the proposed model each year, as new harvest areas are added to the pool and
234 demand and road network accessibility information are updated. In fact with the proposed
235 model in this paper, we suggest a plan for the upcoming year but covering a full five-year
236 horizon in the planning process; in this way we can guarantee a balanced use of wood
237 resources in terms of the considered criteria over a longer period.

238 In order to systematically develop/implement forest management policies, the land
239 covered with forest is divided into forest management regions and then subdivided into
240 forest management units (FMU) consisting of several harvest areas. The planning process
241 under study is being considered at the forest management unit level, and each FMU is
242 responsible for supplying the wood processing mills within its territory.

243 Moreover, in order to highlight the potential of using a multi-objective planning strategy,
244 the proposed model is tested for an FMU in the province of Québec and is compared to a
245 commonly considered planning strategy for tactical forest management which can be
246 described as follows. Before the Sustainable Forest Development Act came to effect, the
247 wood-processing plants that had supply and forest management agreements with the
248 government were responsible for forest planning to obtain their required supply; at that
249 time the MFFP was only responsible for overseeing the planning activities and eventually
250 to consent to the forest management plans produced by the holders of agreement.
251 Currently, planning by the MFFP is being done mostly manually with the help of a
252 number of tools which is a very complex and time-consuming procedure. Due to the
253 complexity of manual planning process, it is very difficult to compute a manual solution
254 for the developed case; instead we formulate an optimization model as a close simulator
255 of the manual procedure in which the objective is deemed to be satisfying mills' demand
256 for the upcoming year with the least possible cost. The optimization model named
257 MinCost mimics such a strategy in which the total purchasing and transportation cost
258 during year 1 is minimized given the same constraints for the proposed multi-objective
259 model. It also has to be noted that often a manual plan is more expensive than an
260 optimized plan. In other words, a manual solution for the considered case in this study

could be expected to be much more costly than the solution obtained from MinCost model.

3. Solution approach

To solve multiple objective optimization problems, there are two well-known approaches: weight method and ε -constraint method. The ε -constraint method chooses the highest priority criterion (that overrides the other criteria) as the objective function, and treats the lower priority criteria as constraints. However, often this approach either rules out many good solutions or leads to infeasibility if the bounds in the constraints are not chosen correctly. Since in this planning problem no single criterion can be presumed to fully override the other two, the ε -constraint method is not a suitable methodology to adopt.

On the other hand, GP considers multiple objectives simultaneously in the optimization process. In a general GP approach a specific numeric goal for each of the objectives will be established, then a solution that minimizes the weighted sum of deviations of the objective functions from their respective goals will be sought. In fact the three criteria under study have very different nature and numeric magnitude, hence, in order for adequate functioning of the GP, the respective objective functions need to be normalized. The use of Nadir theory and Payoff Table method would overcome this issue of incommensurability of the three considered objectives. Additionally, according to the MFFP, the three chosen criteria are considered to be of the same level of importance and since the respective objective functions would also be normalized, this choice of the MFFP regarding the relative importance of the criteria can be applied with confidence

that every one of the criteria will equally impact the final solution. Also, the target value of each criterion is established by computing its average value (this will be explained more in the following sections). Thus, in this work we opted for GP accompanied by the Nadir theory as a suitable solution methodology for this problem setting.

We first establish a target value for each of the three optimization criteria considered, and then three individual models will be solved to minimize the maximum deviation of each criterion from the target value among all time periods. Finally, in another model, the weighted sum of deviation of formulated objective functions from their respective optimal values will be minimized. The solutions to these models will be presented in tables to demonstrate the performance of each criterion for each of the single objectives as well as for the multi-objective function.

We employ the knowledge of Nadir objective vector and Payoff Table method for the normalization purpose in the entire Pareto-optimal region. Consider two minimization objective functions f_1 and f_2 . By definition, for minimization functions, the optimal objective vector represents the lower bound of each objective in the entire feasible search space and the Nadir objective vector, represents the upper bound of each objective in the entire Pareto-optimal set (not in the entire search space) (Deb, 2001). For instance, the Nadir value of f_1 equals to its value in the optimal solution of f_2 (i.e., $x^{*(2)}$): $f_1^{nad} = f_1(x^{*(2)})$. Eq. (1) shows how objective function f_1 is normalized in the entire Pareto-optimal region by means of its optimal and Nadir values.

$$f_1^{norm} = \frac{f_1 - f_1^{optimal}}{f_1^{nad} - f_1^{optimal}} \quad (1)$$

It is not a straightforward task to calculate the exact value of the Nadir point for more than two objectives because the Nadir point requires the knowledge of extreme Pareto-optimal solutions (Deb and Miettinen, 2010). A standard approach to estimate the Nadir objective values is the Payoff Table method. First the individual optimum solutions are computed $(x^{*(1)}, \dots, x^{*(p)})$, then a Payoff Table is constructed through computing the objective values at these optimal solutions, and eventually estimated Nadir point of each e.g. minimization objective will be its highest value in the table. For more details on this technique, interested readers are referred to Deb and Miettinen, (2010).

4. Model formulation

In this section we present the proposed deterministic MINLP, MIP and linear programming (LP) formulations which model the described tactical forest management planning problem.

In order to develop a sustainable tactical plan which consumes the available wood supply over several years robustly, the proposed multi-objective model aims to balance the average value of three specific criteria in each time period against their respective target values. The identified criteria are average unit purchasing and transportation cost, average volume per stem (i.e., representing average stem size) and average volume per hectare.

The target values are set by the MFFP by calculating the average value of each criterion (except for the transportation cost) over all given harvest areas; the logic behind it was that the harvest areas in each FMU have similar characteristics, so over the years the new harvest areas that will be added to the register will have similar attributes on average. In

order to establish a target for the transportation cost, a separate classic constrained transportation model is solved to obtain the minimum average transportation cost as target ($\overline{c^{tr}}$). The transportation model is an LP developed in a single-period context; it minimizes the total transportation cost of allocating all the available wood in all harvest areas to mills, constrained to some conventional constraints about mills' minimum demand and harvest areas' capacity as well as the constraints related to mills' specific requests regarding some characteristics of their allocation. The obtained optimal flow of stems among harvest areas and mills is used to compute the target average unit transportation cost.

The length of the planning horizon is 5 years. Since foreseeing mill demand for more than one year in advance is very difficult, the first year is considered as the business period and only the decisions made in this period will be used in practice; the last four years, on the other hand, are aggregated to one anticipation period and the relevant decisions are used solely for the purpose of anticipating the impact of business decisions over a longer period of time.

Additionally, due to the arbitrary composition of available volume of wood at harvest areas and the minimum and maximum mills' annual demand, not all the available wood in any group of selected harvesting areas during period 1 can be allocated to mills as this would exceed the mills' maximum demand limits. Hence, in order to control the volume of uncut trees left inside the selected harvest areas during time period 1, a separate optimization model is solved to obtain the minimum volume that will inevitably be left uncut during period 1 (l^{min}). Then a planner-defined multiplication of that volume will set an upper bound for volume left uncut inside selected harvest areas during period 1

(Eq. 15). In addition, it is assumed that the uncut trees inside selected harvest areas during period 1 must be harvested and allocated to mills in the subsequent time period.

Despite some aspects of the defined problem being tailored to the Québec situation and the implementation of the new Act, we believe the proposed model and solution approach could easily be adapted to address similar problems in any other case. The complete list of indices, sets, parameters and decision variables is given in Table 1.

Procedure to implement GP for the defined problem in Québec context

Here we provide the step-by-step procedure required to implement GP approach for the defined problem in the Québec context.

Step 1: Since no demand information for the anticipation period is available, an optimization model needs to be solved to determine the maximum multiplication of the min & max mill demand during the business period that could be satisfied with the given harvest areas during the anticipation period.

Step 2: Solve the model that minimizes the wood left uncut inside selected areas during year 1. The purpose is to limit the volume that will inevitably be left uncut inside selected harvest areas during each time period 1.

Step 3: Solve a constrained transportation model to obtain the minimum average unit transportation cost that sets the respective target value in the following models.

Step 4: Solve the model associated to each of the three criteria individually.

Step 5: Solve the multi-objective model.

Constraints

There are different motivations for the constraints; here we present the ones which are relevant to the current planning process at the MFFP. Eq. (2) makes sure during time period 1 the allocated volume of each stem type to each mill is between its minimum and maximum annual demand. Since no demand information for year 2-5 was available, we have modeled the mill demand during the anticipation period as follows. We introduced a parameter β : it is assumed that the minimum and maximum demand of each mill during the anticipation period is β times its min and max demand during period 1. In other words each mill demand range in the anticipation period is modeled equally proportionate to the range of its demand during business period (Eq. 3). However, it is important to have the same value of β for all of our models; otherwise, different demand structure for period 2 in different models would hinder the comparability of the respective solutions. In order to determine an appropriate value for β , we solved a separate model to determine what the maximum possible value of β is, given all relevant constraints.

$$de_{kp}^{min} \leq \sum_{a \in A} X_{akpt} \leq de_{kp}^{max} \quad \forall k \in K_p, p \in P, t = 1 \quad (2)$$

$$\beta de_{kp}^{min} \leq \sum_{a \in A} (X_{akpt} + X_{akpt}^2) \leq \beta de_{kp}^{max} \quad \forall k \in K_p, p \in P, t = 2 \quad (3)$$

Eqs. (4-5) respectively assure that the average transportation distance and average unit purchasing and transportation cost are kept less than a maximum limit specified by the mills. Also, some mills have been installed very close to the forest while others are located much further; so, in order to have some level of fairness among all the mills, the MFFP enforces a minimum transportation distance (di_{kp}^{min}) as well as a minimum average unit cost (c_{kp}^{min}) on the mills known to be located relatively very close to the

forest vicinity, while for the rest these lower bounds are set to zero. Eq. (6) ensures the average size of allocated stems is in alignment with what mills need.

$$\begin{aligned}
 di_{kp}^{min} \sum_{j \in J_{kp}} (X_{jkpt} + X_{jkpt}^2) &\leq \sum_{j \in J_{kp}} di_{jkp} (X_{jkpt} + X_{jkpt}^2) \\
 &\leq di_{kp}^{max} \sum_{j \in J_{kp}} (X_{jkpt} + X_{jkpt}^2) \quad \forall k \in K_p, p \in P, t \in T
 \end{aligned} \quad (4)$$

$$\begin{aligned}
 c_{kp}^{min} \sum_{j \in J_{kp}} (X_{jkpt} + X_{jkpt}^2) &\leq \sum_{j \in J_{kp}} (c_j^{pur} + c_{jkp}^{tr}) (X_{jkpt} + X_{jkpt}^2) \\
 &\leq c_{kp}^{max} \sum_{j \in J_{kp}} (X_{jkpt} + X_{jkpt}^2) \quad \forall k \in K_p, p \in P, t \in T
 \end{aligned} \quad (5)$$

$$\begin{aligned}
 st_{kp}^{min} \sum_{j \in J_{kp}} (X_{jkpt} + X_{jkpt}^2) &\leq \sum_{j \in J_{kp}} st_{ap} (X_{jkpt} + X_{jkpt}^2) \\
 &\leq st_{kp}^{max} \sum_{j \in J_{kp}} (X_{jkpt} + X_{jkpt}^2) \quad \forall k \in K_p, p \in P, t \in T
 \end{aligned} \quad (6)$$

Each stem type includes a number of species; however, mills may accept to receive only a particular percentage range ($\rho_{spo}^{min}, \rho_{spo}^{max}$) of their annual allocation of a specific stem type to be of a specific species and this matter has been modeled in Eq. (7).

$$\begin{aligned}
 \rho_{kpo}^{min} \sum_{j \in J_{kp}} (X_{jkpt} + X_{jkpt}^2) &\leq \sum_{j \in J_{kp}} \rho_{jpo} (X_{jkpt} + X_{jkpt}^2) \\
 &\leq \rho_{kpo}^{max} \sum_{j \in J_{kp}} (X_{jkpt} + X_{jkpt}^2) \quad \forall k \in K_p, p \in P, t \in T, o \in O_p
 \end{aligned} \quad (7)$$

Eqs. (8-10) ensure that the total allocated volume of a stem type from a specific harvesting area in each time period does not exceed its available volume at that area.

395 During period 1 Eq. (8) allows some volume of wood (L_{apt}) to be left inside the selected
 396 harvest areas, and Eq. (9) assures this amount will be harvested and allocated during the
 397 following time period. In the anticipation period, Eq. (10) ensures no more than the
 398 available volume inside selected areas can be allocated from those areas. Eq. (11) simply
 399 states the assumption that the initial wood (remaining from before the current planning
 400 horizon) that must be allocated during time period 1 is zero.

$$\sum_{s \in S} X_{aspt} + L_{apt} = v_{ap} Y_{at} \quad \forall a \in A, p \in P, t = 1 \quad (8)$$

$$\sum_{s \in S} X_{aspt}^2 = L_{ap(t-1)} \quad \forall a \in A, p \in P, t \in T \quad (9)$$

$$\sum_{s \in S} X_{aspt} \leq v_{ap} Y_{at} \quad \forall a \in A, p \in P, t = 2 \quad (10)$$

$$L_{ap(t-1)} = 0 \quad \forall a \in A, p \in P, t = 1 \quad (11)$$

401 The MFFP annually grants a limited budget for silvicultural treatment to support and
 402 encourage companies following specific prescriptions inside selected harvest areas. Eqs.
 403 (12-13) restrict this subsidy to the annual limit during business period and to β times the
 404 annual limit during the anticipation. Eq. (14) ensures each harvesting area will be
 405 selected at most once during the whole planning horizon.

$$\sum_{a \in A} b_a Y_{at} \leq b \quad \forall t = 1 \quad (12)$$

$$\sum_{a \in A} b_a Y_{at} \leq \beta b \quad \forall t = 2 \quad (13)$$

$$\sum_{t \in T} Y_{at} \leq 1 \quad \forall a \in A \quad (14)$$

Eq. (15) restricts the volume of uncut trees left at the selected harvest areas during period 1 to a planner-defined multiplication (α) of the minimum amount that will inevitably be left (l^{min}). In the anticipation period we limit the uncut trees to the 20% of total maximum mill demand in period 2 minus the leftover coming from the business period (Eq. (16)).

$$\sum_{a \in A} \sum_{p \in P} v_{ap} Y_{at} - \sum_{a \in A} \sum_{s \in S} \sum_{p \in P} X_{aspt} \leq \alpha l^{min} \quad \forall t = 1 \quad (15)$$

$$\begin{aligned} \sum_{a \in A} \sum_{p \in P} v_{ap} Y_{at} - \sum_{j \in J_{kp}} \sum_{k \in K_p} \sum_{p \in P} (X_{jkpt} + X_{jkpt}^2) \\ \leq 0.20 \left(\beta \sum_{k \in K_p} \sum_{p \in P} de_{kp}^{max} \right. \\ \left. - \left(\sum_{a \in A} \sum_{p \in P} v_{ap} Y_{a(t=1)} - \sum_{a \in A} \sum_{s \in S} \sum_{p \in P} X_{aspt(t=1)} \right) \right) \quad \forall t = 2 \quad (16) \end{aligned}$$

Finally, Eqs. (17-18) enforce the non-negativity and binary restriction on the decision variables.

$$X_{aspt} \geq 0, X_{aspt}^2 \geq 0, L_{ap(t-1)} \geq 0 \quad \forall a \in A, s \in S, p \in P, t \in T \quad (17)$$

$$Y_{at} \in \{0,1\} \quad \forall a \in A, t \in T \quad (18)$$

Objective functions

414 The objective function f^{uncut} is to find the minimum volume of trees that will inevitably
 415 be left uncut inside the selected harvest areas during period 1. The respective model is an
 416 MIP.

$$\text{Min } f^{uncut} \quad (19)$$

$$\text{Subject to: } f^{uncut} = \sum_{a \in A} \sum_{p \in P} v_{ap} Y_{at} - \sum_{a \in A} \sum_{s \in S} \sum_{p \in P} X_{aspt} \quad \forall t = 1 \quad (20)$$

417 In order to ensure that the criteria are as close as possible to the defined targets in both
 418 periods we designed the objective functions to minimize the maximum deviation of each
 419 criterion from target between the two time periods. In the objective function f^1 we have
 420 two cost components. The first component is purchasing cost which comprises costs
 421 related to all forest operations. The second one is the cost of transporting stems to the
 422 mills. The f^1 is to minimize the maximum deviation of unit purchasing plus
 423 transportation cost during each time period from their respective target value.

$$\text{Min } f^1 \quad (21)$$

Subject to :

$$f^1 \geq f_t^{1+} + f_t^{1-} \quad (22)$$

$$\begin{aligned} & f_t^{1+} - f_t^{1-} \\ &= \left(\sum_{j \in J_{kp}} \sum_{k \in K_p} \sum_{p \in P} (c_{jkp}^{tr} + c_j^{pur}) (X_{jkpt} + X_{jkpt}^2) / \sum_{j \in J_{kp}} \sum_{k \in K_p} \sum_{p \in P} (X_{jkpt} + X_{jkpt}^2) \right) \\ & - (\overline{c^{tr}} + \overline{c^{pur}}) \end{aligned} \quad (23)$$

Objective function f^2 is to minimize the maximum deviation of average volume per stem for the allocated volume during each time period from its target value. The objective function f^3 minimizes the maximum deviation of average volume per hectare of selected harvest areas during each time period from its target value. In all the cases the absolute value of deviation is considered, e.g., $f_t^{1+} + f_t^{1-}$ represents the absolute value of right-hand side of Eq. (23).

$$\text{Min } f^2 \quad (24)$$

Subject to:

$$f^2 \geq f_t^{2+} + f_t^{2-} \quad (25)$$

$$f_t^{2+} - f_t^{2-} = \sum_{j \in J_{kp}} \sum_{k \in K_p} \sum_{p \in P} (st_{ap})(X_{jkpt} + X_{jkpt}^2) / \sum_{j \in J_{kp}} \sum_{k \in K_p} \sum_{p \in P} (X_{jkpt} + X_{jkpt}^2) - \bar{st} \quad (26)$$

$$\text{Min } f^3 \quad (27)$$

Subject to:

$$f^3 \geq f_t^{3+} + f_t^{3-} \quad (28)$$

$$f_t^{3+} - f_t^{3-} = \sum_{a \in A} vph_a ar_a Y_{at} / \sum_{a \in A} ar_a Y_{at} - \overline{vph} \quad (29)$$

The multi-objective function f^{MO} (Eq. 31) minimizes the weighted-sum of the normalized deviation of f^i from its optimal value f^{i*} for each $i \in I$. The f_i^{Nadir} represents the Nadir value of objective function i , obtained by the Payoff Table method.

433 The four single-objective and multi-objective functions are non-linear functions leading
434 to MINLP models.

$$\text{Min } f^{MO} \quad (30)$$

$$\text{Subject to: } f^{MO} = \sum_{i \in I} w_i \left(\frac{f^i - f^{i*}}{f_i^{Nadir} - f^{i*}} \right) \quad (31)$$

435 Also, all the constraints explained earlier are common for the models related to objective
436 functions: $f^i \forall i \in I, f^{MO}$ and f^{uncut} ; except for f^{uncut} model the equation (15) must be
437 excluded as l^{min} is the optimum objective value of f^{uncut} model.

438 ***Linearization methodology to solve the MINLP models***

439 Generally the MINLP problems are known to be difficult to solve with commercial
440 solvers even for small instances. Hence, we propose a linearization approach to obtain
441 good-quality solutions for MINLP models in large instances within a reasonable time.

442 This approach is based on fixing the denominator of the nonlinear objective functions
443 (converting them to linear ones) and then trying to find the best solution around the fixed
444 factors. The denominators of f^1 and f^2 are the allocated volume in each time period; and
445 for the f^3 the denominator is the sum of areas of selected harvest areas in each time
446 period. The proposed linearization procedure is explained as follows.

447 Step 1: Solve an MIP model that minimizes the total cost over the entire planning horizon
448 to obtain a proper base value for the denominators of the nonlinear functions.

Step 2: The denominators of Eqs. 23 & 26 are fixed to γ_t and the denominator of Eq. 29 is fixed to ρ_t . New constraints are added (Eqs. (33-37)). Solve the transformed MIP models and follow the GP implementation procedure explained earlier.

In order to control the flexibility in the values of total allocation per period and total areas of selected harvest areas per period (i.e. denominators of the nonlinear functions) the constraints Eqs. (33-37) are introduced. These constraints allow a maximum of $k_t^1\%$ and $k_t^2\%$ deviation in total allocation and total areas of selected harvest areas per period from the fixed values γ_t and ρ_t respectively.

$$\sum_{j \in J_{kp}} \sum_{k \in K_p} \sum_{p \in P} (X_{jkpt} + X_{jkpt}^2) + (S_t^{1+} - S_t^{1-}) = \gamma_t \quad t \in T \quad (33)$$

$$S_t^{1+} + S_t^{1-} \leq k_t^1 \gamma_t \quad t \in T \quad (34)$$

$$\sum_{a \in A} ar_a Y_{at} + (S_t^{2+} - S_t^{2-}) = \rho_t \quad t \in T \quad (35)$$

$$S_t^{2+} + S_t^{2-} \leq k_t^2 \rho_t \quad t \in T \quad (36)$$

$$S_t^{1+}, S_t^{1-}, S_t^{2+}, S_t^{2-} \geq 0 \quad t \in T \quad (37)$$

5. Description of Canadian case study

The study is comprised of a real case (named Case A), of the FMU 07451 inside region 7, Outaouais in western Québec, Canada. The geographical location of the case and the geographical setup of the mills and harvest areas are shown in Figure 1 (a & b). For this case, 107 harvest areas are available in a register that could be used for the planning of supply for 13 wood-processing mills operating in the territory of this FMU. We have 10 sawmills, 2 pulp and paper mills and 1 veneer mill. Seventeen stem assortments have

been defined; each encompasses a small number of species and has one specific application. Among them, two stem types (of about $71,391 \text{ m}^3$) do not have any buyer. In the proposed model we chose to keep them uncut; yet, this fact underlines the need to and the potential in expansion of the existing customer base.

Also, in order to assess the performance of the linearization approach, a smaller case (named Case B) of 23 harvest areas (out of the pool of 107 harvest areas in Case A) is developed. Some key information on the cases A and B are shown in Table 2.

All the required data for the case has been provided by the MFFP and some have particularly been extracted from the simulation software FPInterface developed by FPInnovations, the research and development center of the Canadian forest industry. Table 3 presents a summary of the properties of the harvest areas in the Case A.

6. Results and discussion

The developed MINLP, MIP and LP models are implemented in the modeling language AMPL version 2015.12.2.2. The problem for Case A is solved by means of the proposed linearization technique because the MINLP solver BARON proved ineffective. All models are solved by means of either the MINLP solver BARON 16.12.7 or MIP/LP solver CPLEX 12.6.3.0 on a desktop (Windows Server 2012 R2) with 64.0 GB of RAM and 3.5 GHz processor.

The solution for Case A obtained by the proposed linearization approach is presented in Tables 4 & 5. Table 4 shows comparison among single-objective models, multi-objective optimization (MOO) and MinCost strategies in terms of two measures chosen as key performance indicators (KPI): (1) the maximum deviation of average value of each

486 criterion from target between the two time periods in percentage (MDT), (2) the mean
487 deviation of average value of each criterion from target in the two time periods in
488 percentage (MeD). In terms of the size of models, 214 binary variables, 106,000
489 continuous variables and 55,900 constraints have been used in the proposed formulations.

490 From the results shown in Table 4 we observe that the proposed linearization solution
491 procedure has been able to obtain a more balanced plan for Case A relative to MinCost
492 strategy in about five hours while the solver BARON has not been able to solve this case.

493 Often, and in this case also, much more supply is available than the actual demand of
494 business period, enabling the MinCost planning strategy to do high-grading, i.e. to choose
495 the best-located harvest areas, the ones which are more dense in terms of available
496 volume in them per hectare and the ones with more suitable stem size for the upcoming
497 year and to leave the worst; through such a strategy this situation deteriorates every time
498 the problem is resolved. On the other hand by running MOO model every year on a 5-
499 year rolling horizon basis with a replenished register of newly-surveyed harvest areas, an
500 updated road network database and updated demand information, the MFFP would be
501 able to ensure a balanced use of wood supply in terms of the considered criteria over a
502 longer period.

503 *Assessment of the linearization technique*

504 In this section the solution for Case B applying the linearization approach is compared to
505 the solution obtained by means of the commercial solver BARON. In terms of the size of
506 models for Case B, 46 binary variables, 23,080 continuous variables and 12,440
507 constraints have been constructed in the proposed formulations.

The indicator MeD computed for each of the three criteria for MOO strategy solved by BARON vs. the linearization and MinCost alternative are compared in Table 6. As one might expect the MOO model solved by the linearization approach does not perform as well as the BARON solution, but still its proposed plan results in less deviation of the criteria from their respective target than MinCost's plan. It is noteworthy that solution time of the linearization approach is substantially smaller i.e. less than one minute vs. 22.5 hours needed for BARON.

A standard approach to solve the MINLP problems is to choose a scaling factor as a fixed value for the denominator of the nonlinear component. Our linearization approach aims to find a proper scaling factor. Based on a number of tests 5-10% changes in the chosen value of the denominator of nonlinear functions may cause 0.6-9% deviation in the value of those functions. This clearly shows the need to find the proper denominator.

Analyzing the impact of logistics constraints

In order to explore the potential savings in the logistics costs of the whole system, another test has been conducted in which all logistics constraints imposed by the stakeholders were removed from the base multi-objective model. We call this solution, system optimality. For Case B the system's average unit transportation cost over the entire planning horizon decreased by about 4% compared to the base MOO model. It seems preferable to implement the system optimality plan in practice, however, often such harvest area allocation to mills is not perceived as a fair allocation by all companies. Specifically because of deactivating all the logistics constraints in the system optimal model, the mills located very close to the forest will often take advantage of this inherent

benefit of theirs by being allocated to harvest areas very close to them (leading to a relatively very small transportation distance), while other mills located further from the forest have to transport much longer distances to access their supply. Ideally the allocation of system optimal solution should be implemented, but at the same time, in order for the MFFP to overcome the abovementioned issue, it is required to redistribute either the total cost or the extra savings compared to the base model's cost among the mills. This could get done efficiently through game theory models based on e.g. the level of contribution of each mill to finding the better solution for the whole system. Nonetheless, proposition of such game theory models for cost-redistribution is out of the scope of this paper; we refer readers interested in that field of research to the works done by Audy et al. (2012a,b).

7. Conclusions and future works

In this paper, we studied the tactical forest management planning problem over a five-year planning horizon in a multi-period, multi-product and multi-company setting. According to the province of Québec's new Sustainable Forest Development Act, currently the MFFP is the sole party responsible for developing such forest management plans and from its planners' perspective it is of great importance to ensure that all resources are being used in a balanced manner in terms of different criteria over longer period of time (i.e. with the least deviation of criteria from their respective target).

In this research the considered resources were the harvest areas with their specific attributes in terms of size, volume, species composition, and average tree size that should be used robustly. The importance of this matter could be justified by the fact that if the MFFP does not deliberately enforce a balanced tactical plan, due to availability of supply

more than the annual demand any other plan would usually do high-grading of the resources. This is precisely what the proposed MOO model aimed to prevent. Three most important criteria to the MFFP were identified and the main goal was to stabilize them at the same time over the whole planning horizon while satisfying specific constraints. For that purpose, we employed the idea of business and anticipation periods and developed a MOO model based on the GP technique. By comparing the MOO model with the conventional cost-minimization alternative, we observed that the MOO leads to much less deviation of the criteria from their respective target, which is a more stable plan in terms of those criteria over longer period.

Multiple avenues for future development of the presented work are identified. First, the model could be modified to add a fourth optimization criterion in order to control the spatial dispersion of selected harvest areas during each period. Secondly, future research could include aggregation of the FMUs into groups so that the optimization could be performed at the regional level to explore transportation synergies and wood swap (or wood bartering) possibilities. This may give rise to some coordination conflicts among mills and coordination mechanisms must be developed and compared to the current practices with no coordination. Thirdly, since not all harvest areas are accessible through Québec's current road network, the decisions about building new roads or upgrading existing ones have to be made based on when harvesting is expected to occur in the stands served by that road segment and its required accessibility conditions. Moreover, game theoretic models could be applied to present a framework to share associated costs among involved mills in a fair manner.

575 Acknowledgements

576 The authors would like to thank the MFFP specially Mr. Sylvain Dallaire and
577 FPInnovations, for their support in data gathering and participating in rewarding
578 discussions. Also, the authors are grateful for the financial support, in the form of
579 graduate research funding to the first author, provided by the Natural Science and
580 Engineering Research Council of Canada (NSERC) through its Strategic Research
581 Network on Value Chain Optimization and the FORAC research consortium.

Draft

References

- Audy, J.-F., D'Amours, S., and Rönnqvist, M. 2012a. An empirical study on coalition formation and cost/savings allocation. *Int. J. Prod. Econ.* **136**: 13–27. doi: [10.1016/j.ijpe.2011.08.027](https://doi.org/10.1016/j.ijpe.2011.08.027).
- Audy, J.-F., Lehoux, N., D'Amours, S., and Rönnqvist, M. 2012b. A framework for an efficient implementation of logistics collaborations. *International Transactions in Operational Research*. **19**(5): 633–657. doi: [10.1111/j.1475-3995.2010.00799.x](https://doi.org/10.1111/j.1475-3995.2010.00799.x).
- Audy, J.-F., Mobtaker, A., Ouhimmou, M., Marques, A.F., and Rönnqvist, M. 2016. Tactical planning and decision support systems in the forest-based value creation network. *In Forest Value Chain Optimization and Sustainability. Edited by S. D'Amours, M. Ouhimmou, J.-F. Audy, and Y. Feng.* CRC Press/Taylor & Francis. Chapter 10, pp. 239–282. (ISBN: 978-1-4987-0486-1)
- Beaudoin, D., LeBel, L., and Frayret, J.-M. 2007. Tactical supply chain planning in the forest products industry through optimization and scenario-based analysis. *Can. J. For. Res.* **37**(1): 128–140.
- Bouchard, M., D'Amours, S., Rönnqvist, M., Azouzi, R., and Gunn, E., 2017. Integrated optimization of strategic and tactical planning decisions in forestry. *Eur. J. Oper. Res.* **259**(3): 1132–1143. doi: [10.1016/j.ejor.2016.11.022](https://doi.org/10.1016/j.ejor.2016.11.022).
- Carlgren, C.-G., Carlsson, D., and Rönnqvist, M. 2006. Log sorting in forest harvest areas integrated with transportation planning using backhauling. *Scand. J. For. Res.* **21**(3): 260–271. Doi: [10.1080/02827580600739021](https://doi.org/10.1080/02827580600739021).

D'Amours, S., Epstein, R., Weintraub, A., and Rönnqvist, M. 2011. Operations research in forestry and forest products industry. *Wiley Encyclopedia of Operations Research and Management Science*. doi: [10.1002/9780470400531.eorms1044](https://doi.org/10.1002/9780470400531.eorms1044).

Deb, K. 2001. Multi-objective optimization using evolutionary algorithms. vol. 16. John Wiley & Sons. 518 p.

Deb, K., and Miettinen, K. 2010. Nadir point estimation using evolutionary approaches: better accuracy and computational speed through focused search. *In Multiple criteria decision making for sustainable energy and transportation systems. Edited by M. Ehrgott, B. Naujoks, T.J. Stewart and J. Wallenius*. Springer Berlin Heidelberg. pp. 339–354.

Diaz-Balteiro, L., and Romero, C. 2008. Making forestry decisions with multiple criteria: A review and an assessment. *For. Ecol. Manage.* **255**: 3222–3241. doi: [10.1016/j.foreco.2008.01.038](https://doi.org/10.1016/j.foreco.2008.01.038).

Diaz-Balteiro, L., and Romero, C. 2003. Forest management optimisation models when carbon captured is considered: a goal programming approach. *For. Ecol. Manage.* **174**: 447–457. doi: [10.1016/S0378-1127\(02\)00075-0](https://doi.org/10.1016/S0378-1127(02)00075-0).

Ducheyne, E.I., De Wulf, R.R., and De Baets, B. 2004. Single versus multiple objective genetic algorithms for solving the even-flow forest management problem. *For. Ecol. Manage.* **201**(2): 259–273. doi: [10.1016/j.foreco.2004.07.012](https://doi.org/10.1016/j.foreco.2004.07.012).

Duvemo, K., Lämås, T., Eriksson, L.O. and Wikström, P., 2014. Introducing cost-plus-loss analysis into a hierarchical forestry planning environment. *Ann. Oper. Res.* **219**(1): 415–431.

Epstein, R., Morales, R., Seron, J., and Weintraub, A. 1999. Use of OR systems in the Chilean forest industries. *Interfaces*. **29**(1): 7–29.

Ezzati, S., Najafi, A., and Bettinger, P. 2016. Finding feasible harvest zones in mountainous areas using integrated spatial multi-criteria decision analysis. *Land Use Policy*. **59**: 478–491.

Fleischmann, B., Meyr, H., and Wagner, M. 2008. Advanced Planning. *In* Supply Chain Management and Advanced Planning: Concepts, Models, Software and Case Studies. *Edited by* H. Stadtler, and C. Kilger. 4th ed. Springer-Verlag. Chapter 4, pp. 81–106.

Forsberg, M., Frisk, M., and Rönnqvist, M. 2005. FlowOpt – a decision support tool for strategic and tactical transportation planning in forestry. *International Journal of Forest Engineering*, **16**(2): 101–114.

Government of Québec, 2017. Natural resource development-Forests. [accessed 11 August, 2017]

Gautam, S., LeBel, L., and Beaudoin, D. 2016. A hierarchical planning system to assess the impact of operational-level flexibility on long-term wood supply. *Can. J. For. Res.* **47**(4): 424–432.

Hotvedt, J.E., Leuschner, W.A., and Buhyoff, G.J. 1982. A heuristic weight determination procedure for goal programs used for harvest scheduling models. *Can. J. For. Res.* **12**(2): 292–298.

Johansen, U., Werner, A., and Nørstebø, V. 2017. Optimizing the Wood Value Chain in Northern Norway Taking Into Account National and Regional Economic Trade-Offs. *Forests*, **8**(5): 172. doi: 10.3390/f8050172.

Kangas, A., Nurmi, M., and Rasinmäki, J. 2014. From a strategic to a tactical forest management plan using a hierarchic optimization approach. *Scand. J. For. Res.* **29**(1): 154–165.

Kao, C., and Brodie, J.D. 1979. Goal programming for reconciling economic, even-flow, and regulation objectives in forest harvest scheduling. *Can. J. For. Res.* **9**(4): 525–531.

Karlsson, J., Rönqvist, M., and Frisk, M. 2006. RoadOpt: A decision support system for road upgrading in forestry. *Scand. J. For. Res.* **21**(7): 5–15. doi: [10.1080/14004080500487102](https://doi.org/10.1080/14004080500487102).

Kazana, V., Fawcett, R.H., and Mutch, W.E. 2003. A decision support modelling framework for multiple use forest management: the Queen Elizabeth Forest case study in Scotland. *Eur. J. Oper. Res.* **148**(1): 102–115.

Laukkanen, S., Palander, T., Kangas, J., and Kangas, A. 2005. Evaluation of the multicriteria approval method for timber-harvesting group decision support. *Silva Fennica*, **39**(2): 249–264.

Légis Québec, 2016. A-18.1 – Sustainable Forest Development Act <http://legisQuebec.gouv.qc.ca/en/ShowDoc/cs/A-18.1> [accessed 10 October 2016].

Lundström, J., Öhman, K., Perhans, K., Rönqvist, M., and Gustafsson, L. 2011. Cost-effective age structure and geographical distribution of boreal forest reserves. *J. Appl. Ecol.* **48**: 133–142. doi: [10.1111/j.1365-2664.2010.01897.x](https://doi.org/10.1111/j.1365-2664.2010.01897.x).

Lundström, J., Öhman, K., Rönqvist, M., and Gustafsson, L. 2014. How reserve selection is affected by preferences in Swedish boreal forests. *For. Policy Econ.* **41**: 40–50. doi: [10.1016/j.forpol.2013.12.007](https://doi.org/10.1016/j.forpol.2013.12.007).

MFFP, 2016. Rigorous and Adaptive Forest Management – Main highlights <https://www.mffp.gouv.qc.ca/english/forest/understanding/understanding-forest.jsp> [accessed 10 April 2016].

MFFP, 2016. The Sustainable Forest Development Act — A Renewed Form of Stewardship <https://www.mffp.gouv.qc.ca/english/publications/forest/understanding/fiche-role-responsabilite-en.pdf> [accessed 1 October 2016].

Ouhimmou, M., D'Amours, S., Ait-Kadi, D., Beauregard, R., and Chauhan, S.S. 2008. Furniture supply chain tactical planning optimization using a time decomposition approach. *Eur. J. Oper. Res.* **189**(3): 952–970. doi: [10.1016/j.ejor.2007.01.064](https://doi.org/10.1016/j.ejor.2007.01.064).

Rönqvist, M., D'Amours, S., Weintraub, A., Jofre, A., Gunn, E., Haight, R.G., Martell, D., Murray, A.T., and Romero, C. 2015. Operations Research challenges in forestry: 33 open problems. *Ann. Oper. Res.* **232**(1): 11–40. doi: [10.1007/s10479-015-1907-4](https://doi.org/10.1007/s10479-015-1907-4).

Troncoso, J., D'Amours, S., Flisberg, P., Rönqvist, M., and Weintraub, A. 2015. A mixed integer programming model to evaluate integrating strategies in the forest value chain—a

case study in the Chilean forest industry. Can. J. For. Res. **45**(7): 937–949. doi:
[10.1139/cjfr-2014-0315](https://doi.org/10.1139/cjfr-2014-0315)

Draft

Tables

Table 1. List of indices, sets, parameters and decision variables of the model

Sets and indices	Definition
$a \in A$	Set of harvest areas
$s \in S$	Set of wood-processing facilities (i.e. sawmill, pulp & paper mill, veneer mill)
$p \in P$	Set of products (our definition of products includes only logs)
$t \in T = \{1, 2\}$	Set of time periods (i.e. business and anticipation periods)
$j \in J_{sp}$	Subset of harvest areas that have accessibility to mill s for transporting product p through a well-functioning road network, ($J_{sp} \subset A$)
$k \in K_p$	Subset of mills that have a positive demand for product p , ($K_p \subset S$)
$o \in O_p$	Set of species included in product type p
$i \in I = \{1, 2, 3\}$	Set of objective functions representing the three optimization criteria considered
Parameters	Definition
v_{ap}	Volume of product p available at harvest area a (m^3)
st_{ap}	Average volume per stem of product p at harvest area a (m^3/stem)
ρ_{apo}	Percentage of total volume of product p existing in harvest area a that is of species $o \in O_p$
vph_a	Average volume per hectare in harvest area a (m^3/ha)
ar_a	Area of harvest area a (ha)
c_a^{pur}	Purchasing cost of a unit of any type of product at harvest area a ($\$/m^3$); this cost component includes all forest operations cost in area a , excluding transportation cost
c_{jsp}^{tr}	Transportation cost of a unit of product p from harvest area $j \in J_{sp}$ to mill s ($\$/m^3$)
di_{jsp}	Transportation distance for product p from harvest area $j \in J_{sp}$ to mill s (km)
b_a	Subsidy granted by MFFP to ensure harvest area a will be cut based on specific guidelines
b	Annual subsidy budget (it is assumed this budget is fixed during the planning horizon)
α	A planner-defined real number ($\alpha > 1$)
w_i	Relative importance of objective function i
n	Number of harvest areas
<i>Parameters related to mills' requirements</i>	
$de_{kp}^{min}, de_{kp}^{max}$	Minimum/maximum mill k 's annual demand (m^3) of product p
$c_{kp}^{min}, c_{kp}^{max}$	Minimum/maximum unit purchasing & transportation cost of product p for mill k

(Continued)

Table 1- (Continued)

Parameters	Definition
$di_{kp}^{min}, di_{kp}^{max}$	Minimum/maximum average transportation distance of product p between mill k and its assigned harvest areas
$st_{kp}^{min}, st_{kp}^{max}$	Minimum/maximum avg. volume per stem of product p for mill k
$\rho_{spo}^{min}, \rho_{spo}^{max}$	Minimum/maximum percentage of product p 's allocation to mill s to be of specie $o \in O_p$
<i>Other input parameters</i>	
$\overline{c^{pur}} = \frac{\sum_a \sum_p v_{ap} c_a^{pur}}{\sum_a \sum_p v_{ap}}$	Weighted-average of purchasing cost considering all harvest areas (target value)
$\overline{st} = \frac{\sum_a \sum_p v_{ap} st_a}{\sum_a \sum_p v_{ap}}$	Weighted-average of average volume per stem considering all harvest areas (target value)
$\overline{vph} = \frac{\sum_a ar_a vph_a}{\sum_a ar_a}$	Weighted-average of average volume per hectare considering all harvest areas (target value)
$\overline{c^{tr}}$	Minimum average unit transportation cost (target value)
l^{min}	Optimum/minimum value of f^{uncut}
β	Maximum multiplication of the min & max mills demand during the business period that could be satisfied with the given harvest areas during the anticipation period
<i>Parameters used in the linearization</i>	
γ_t	Total allocated volume in period t (Step 1 of Linearization)
ρ_t	Total area of selected harvest areas in period t (Step 1 of Linearization)
k_t^1, k_t^2	Maximum allowed percentage of deviation from γ_t and ρ_t respectively
Decision variables	Definition
X_{aspt}	Flow of product p from harvest area a to mill s during time period t (m^3)
X_{aspt}^2	Flow of product p remaining inside harvest area a (i.e., left uncut at forest during time period $t - 1$) to mill s during time period $t = 2$ (m^3); when $t = 1$ this variable is set to zero.
$L_{ap(t-1)}$	Volume of product p that is left uncut at harvest area a during time period $(t - 1)$ that must be cut and allocated during period t (m^3)
Y_{at}	Binary decision variable equals 1, if harvest area a is selected to be harvested during time period t , 0 otherwise.
<i>Decision variables used in the linearization</i>	
S_t^{1+}, S_t^{1-}	Slack variables (up & down) to measure the deviation from γ_t
S_t^{2+}, S_t^{2-}	Slack variables (up & down) to measure the deviation from ρ_t

Table 2. Information on the cases A and B regarding the dimension of the planning problem and some other relevant data.

Aspect	Case A	Case B
Number of harvest areas	107	23
Number of wood-processing mills	13	13
Aggregated demand range of all mills (m^3)	[435,180 – 495, 265]	[435,180 – 495, 265]
Available supply (m^3)	3,707,179	695,347
Unwanted stem types (m^3)	71,391	18,745
Number of stem types	17	17
Number of species	15	15
Average tree size ($m^3/stem$)	0.22	0.2455
Total area of all harvest areas (ha)	41,696	7,629
Number of years in the business period	1	1
Number of years in the anticipation period	4	4
The length of planning horizon (years)	5	5

Table 3. Summary of harvest areas’ properties for Case A

	Volume (m^3)	Area (ha)	Avg. stem size (m^3)	S.T.* budget (\$)
Average	30,233	332	0.2455	114,295
Min	2,466	25	0.02	16,328
Max	79,479	722	5.82	300,985
SD†	22,918	224	0.72	101,272

*Silvicultural Treatment, †Standard Deviation

Draft

Table 4. Comparison among single-objective models, MOO and MinCost strategies for Case A

		Case A		
		C1 [*]	C2 [†]	C3 [‡]
f^1 (linearization)	Target	48.66	0.2201	88.91
	t_1	49.20	0.1979	93.41
	t_2	48.54	0.2239	88.96
	MDT [§]	1.11%	10.07%	5.06%
	MeD	0.67%	5.91%	2.56%
f^2 (linearization)	t_1	49.08	0.2200	90.38
	t_2	49.81	0.2136	88.28
	MDT	2.36%	2.91%	1.65%
	MeD	1.61%	1.48%	1.18%
f^3 (linearization)	t_1	49.40	0.2357	90.86
	t_2	49.95	0.1984	90.01
	MDT	2.64%	9.84%	2.19%
	MeD	2.09%	8.48%	1.71%
MOO (linearization)	t_1	49.71	0.2249	90.86
	t_2	48.64	0.2198	90.61
	MDT	2.15%	2.20%	2.19%
	MeD	1.10%	1.15%	2.05%
MinCost	t_1	47.69	0.2147	94.27
	t_2	50.34	0.2088	88.31
	MDT	3.45%	5.12%	6.02%
	MeD	2.72%	3.79%	3.35%

Note: $k_t^1 = k_t^2 = 20\% \forall t \in T, \gamma_{t=1} = 449,777.42 (m^3), \gamma_{t=2} = 522,012.04 (m^3), \rho_{t=1} = 5,341.91(ha), \rho_{t=2} = 6,898.88(ha), \alpha = 6.5, \beta = 1.2$.

*Average purchasing & transportation cost (\$/m³), †Average stem size (m³/stem), ‡Average volume per ha (m³/ha), §Maximum deviation from target between the two time periods (%), ||Mean deviation from target between the two time periods (%).

Table 5. Solution comparison between MOO (linearization method) and MinCost for Case A

		Case A	
		MOO	MinCost
Harvested and transported volume (m^3)	t_1	440,317	434,701
	t_2	522,279	546,808
Volume left uncut inside selected harvest areas (m^3)	t_1	28,056	66,496
	t_2	113,937	106,065
Average unit purchasing cost ($\$/m^3$)	t_1	32.68	31.25
	t_2	31.79	32.84
Average unit transportation cost ($\$/m^3$)	t_1	17.03	16.45
	t_2	16.84	17.50
Avg. cost over the entire planning horizon	T	49.13	49.17
Purchasing cost	t_1	14.39	13.58
	t_2	16.60	17.96
Transportation cost	t_1	7.50	7.15
	t_2	8.79	9.57
Total cost	t_1	21.89	20.73
	t_2	25.39	27.53
Average transportation distance (km/m^3)	t_1	203.76	199.27
	t_2	200.78	206.05
Total area of selected harvest areas (ha)	t_1	5308.53	5467.66
	t_2	6879.62	6805.86
Number of selected harvest areas	t_1	18	19
	t_2	18	15

Note: All costs are given in CAD millions.
Used parameters: $\alpha = 6.5$, $\beta = 1.2$, $w_1 = w_2 = w_3 = 1/3$, $l^{min} = 11,088.56 (m^3)$

Table 6. Comparing MOO and MinCost strategies for Case B solved by BARON & linearization approach

		Case B		
		C1 [*]	C2 [†]	C3 [‡]
MOO (BARON)	MeD [§]	0.49%	4.38%	1.1%
MOO (linearization)	MeD	2.08%	4.56%	6.49%
MinCost	MeD	4.06%	7.55%	6.57%

Note: used parameters are $\alpha = 1.5, \beta = 0.44, k_t^1 = k_t^2 = 30\% \forall t \in T, \gamma_{t=1} = 436,839.94 (m^3), \gamma_{t=2} = 191,268.45 (m^3), \rho_{t=1} = 5,294.7 (ha), \rho_{t=2} = 2,190.16(ha)$.

*Average purchasing & transportation cost (\$/m³), †Average stem size (m³/stem), ‡Average volume per ha (m³/ha), §Mean deviation from target between the two time periods (%).

Figure 1 : Geographical location of the case under study