Economic Development Prospects of Forest-Dependent Communities: Analyzing Trade-offs Using a Compromise-Fuzzy Programming Framework

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Many aboriginal communities look to forest resources for short- and long-term employment, adequate timber for mills, an even flow of wood fiber for community stability, and financial returns for economic diversification. We address these conflicting objectives using multiple-objective programming. We show how compromise programming can be used to set bounds on fuzzy membership functions, and illustrate the difference between crisp and fuzzy weighting of objectives. Economic development outcomes obtained using compromise and fuzzy programming greatly improve upon those associated with the even-flow of timber rule of thumb. Yet, timber extraction is an inadequate driver of economic development in rural communities.

Key words: multiple criteria decision making, resource-dependent communities, uncertainty.

In Canada, federal and provincial governments have historically promoted economic development in rural regions via the exploitation of natural resources. Forests played a key role in that development and continue to be looked upon to bring prosperity to some 300 forest-dependent communities, many of which are aboriginal. Some 80% of First Nation communities rely on forestry and related businesses as their main economic activity and source of earned income, and residents have few employment options other than those linked directly or indirectly to natural resource exploitation (Natural Resources Canada 2006, p. 54). Provincial governments set the overarching policy related to forest management as they own some 95% of exploitable timber resources. As a management tool, they have adopted even-flow of timber as the primary mechanism for implementing stability of fiber for mills, employment in forest-level activities (community stability), and government revenues. Because even-flow harvests are based on mean annual timber growth over some planning horizon, environmental sustainability is also addressed.

There are problems with this approach to economic development, however. First, forests are more than just a driver of development as they also provide nontimber forest amenities that may be incompatible with timber exploitation. Second, even flow ignores the business cycle as too much timber is harvested when prices are low and too little is harvested when prices are high. Finally, the forest resource base may simply be inadequate, with resource constraints too onerous to satisfy development needs. Resource dependent communities may need to trade off short- versus long-term employment depending on the timing of harvests and investments in growing stock. Employment in forestry may need to be sacrificed to gain higher resource rents, which can then be invested to diversify the economy (or help people move to larger centers with greater employment opportunities). Essentially, forest management policies require the balancing of complex environmental, employment and economic development objectives over long periods of time, because decisions made today affect the options available in the future. In this regard, the current policy of ensuring a stable timber supply may

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be an effective rule-of-thumb policy for balancing environmental, employment and other objectives. But is it nonoptimal, leading to unacceptable trade-offs?

To address this issue, we develop a decision framework for balancing conflicting objectives that employs compromise and fuzzy programming, and compares results from these approaches with those of the current policy of maintaining an even-flow of timber to mills. While compromise and fuzzy programming have separately been applied to a variety of problems, Duval and Featherstone (2002) were to our knowledge the first to employ both in an agricultural setting with an application to a portfolio selection problem with two objectives, maximizing return and minimizing risk. Duval and Featherstone compared compromise programming and fuzzy programming to a traditional mean-variance (EV) approach. A direct comparison of models is possible in the portfolio selection case because any solution to the two-objective optimization problem depends only on one weighting coefficient and can be graphically presented.[1] The economic development problem for a forest-dependent community involves more than two objectives, there is no straightforward equivalent of a risk aversion parameter as in EV analysis, and elicitation of objective weights is difficult. These issues pose particular challenges for multiple-objective programming that we address in the current study. Further, unlike Duval and Featherstone, who used the results from single-objective solutions to construct fuzzy membership functions, we employ the results of compromise programming to construct fuzzy membership functions. This novel approach results in solutions that balance trade-offs among multiple objectives under uncertainty without the explicit need to elicit risk attitudes from decision makers (although some notion of preferences among objectives would still be required), while providing a higher degree of satisfaction (comfort) with the resulting trade-off.

In this article, we consider the opportunities and obstacles that face an aboriginal community in northern Alberta that strives to support a growing population by taking on responsibilities related to "logging, silviculture, and the provision of other forest management services" (First Nations Forestry Program 2007a, p. 7). The development challenge is to balance objectives so as to maintain a viable and healthy community over the long term. We proceed in the next two sections by discussing the use of multiple-objective modeling approaches in the context of a rural development problem, and providing the programming framework that we use to examine possible development strategies for an aboriginal, forest-dependent community. We then provide background information and data for our application and our modeling results. We end with some conclusions about both the development problem and the use of our programming tools.

Multiple-Objective Decision Models

Multiple-objective programming (MOP) emerged in the early 1970s to deal with the simultaneous optimization of several objectives. Because agricultural, resource management, and ecological issues often require the satisfaction of financial, social, and, importantly, biological objectives that can only be considered incommensurable, MOP has increasingly been applied by economists working in these areas. Romero and Rehman (1987) reviewed about 150 applications of multiple-objective programming in natural resource management, but the number of applications has increased tremendously since their study. The main problem that plagues MOP remains to be resolved: the lack of a single unified framework for optimizing over multiple objectives, so solution techniques vary widely.

One way to solve a MOP problem is to construct an aggregated objective function to be optimized. Objectives are combined into a single expression using fixed weights to represent stakeholders' relative importance of various attributes in the utility function (Steuer 1986). This approach has been used in agriculture (Amador, Sumpsi, and Romero 1998; Gómez Limón, Riesgo, and Arriaza 2004; Bazzani 2005) and forestry (Ananda and Herath 2005).

A psychologically appealing idea is to seek solutions that minimize the distance between the attained levels of various objectives and their targets (or most desirable levels). This notion is the basis for multicriteria approaches, such as goal programming,

[1] When the weights are fixed, a subset of Pareto solutions is generated by changing the risk parameter. When the risk parameter is fixed, all solutions can be generated by varying the weight on one of the objectives from 0 to 1, with the other weight adjusted accordingly.

compromise programming and fuzzy programming, which differ in how they define targets and distances in the objective space. Goal programming, introduced by Charnes and Cooper (1977), extends the method of linear programming by setting targets (goals) in the objective space and minimizing deviations from the preset targets. It has been used in many areas of natural resource management, including estimation of optimal fleet size in fisheries (Pascoe and Mardle 2001) and determination of trade-offs between timber and carbon benefits in forest management (Diaz-Balteiro and Romero 2003).

In compromise programming, the best values obtained by single-objective optimization are taken as targets; then, using a family of L_π distance metrics, the weighted distances between realized objective values and targets is minimized (Yu 1973). Compromise programming has been extensively used for decision problems with two objectives. In agriculture, it has been used by Costa and Rehman (2005) to analyze overgrazing in Brazil, and by Duval and Featherstone (2002) to solve a portfolio selection problem. Krcmar, van Kooten, and Vertinsky (2005) used compromise programming to generate different land-use strategies that balanced slow and fast carbon uptake, maintenance of structural diversity in an ecosystem, and net returns to forestry and agriculture, and to examine the associated trade-offs. They investigated more than two objectives and, instead of relying on weights to express the relative importance of objectives, they employed compromise programming with equal weights and two distance metrics to represent the extreme risk-neutral and risk-averse attitudes of decision makers.

Fuzzy programming is used in the multiobjective context when decision makers are uncertain about targets and their attainment, and objectives are best described linguistically. Uncertain targets are defined in terms of fuzzy numbers and a solution is found by maximizing the minimum membership value over all objectives (Zimmermann 1978). For example, in addition to finding an EV-equivalent solution with compromise programming, Duval and Featherstone (2002) solved the portfolio selection problem using fuzzy programming with the vague (imprecise) objectives "high returns" and "low risk." In forest management applications, Hof (1993) used fuzzy programming to demonstrate that large benefits can be gained by relaxing the even-flow constraint typical of sustained-yield policies.

Extracting stakeholder preferences among objectives is the most difficult aspect of the multiattribute utility and the goal and compromise programming approaches. A study that evaluated five weighting methods indicated that users are uncomfortable expressing their preferences in a numerical form (Hajkowicz, Mcdonald, and Smith 2000). Elicitation of weights becomes more difficult with more objectives, and, when the definition of an objective and its realization are unclear, objectives are best described as vague or imprecise. In this article, we do not elicit decision makers' preferences for objectives directly, but we do consider the sensitivity of our results to different weighting schemes.

We propose a framework that combines compromise and fuzzy programming, extending previous work by Krcmar, van Kooten, and Vertinsky (2005) by adding a fuzzy programming component to generate a middle strategy between the extreme risk-neutral and risk-averse outcomes of compromise programming (Ballestero 1997). For the extreme risk-neutral compromise solution, all objectives and regrets (deviations of realized objectives from targets) are treated equally and simultaneously; at the risk-averse extreme, the compromise solution emphasizes only the criterion with the largest regret by minimizing that regret (Freimer and Yu 1976). The Pareto optimal risk neutral and risk averse solutions are used to construct fuzzy membership functions that are then used in fuzzy programming to find the middle ground strategy and, importantly, the degree to which the decision maker might be satisfied with this final compromise.

In contrast to Duval and Featherstone (2002), we have more than two objectives and use compromise programming to identify bounds for constructing the fuzzy sets. Further, since we are interested in determining the development possibilities for a forest-dependent community and what sacrifices are available to them, we compare the results from compromise and fuzzy programming with those of the current even-flow-of-timber policy, which is a rule-of-thumb that governments employ to address compromise over objectives.

Model Formulation: Solving the MOP Problem

A feasible forest management strategy $x \in F$ is evaluated in terms of the objective values (strategy outcomes) $f_q(x)$, $q \in Q$, where

Q is the set of applicable objectives. Unlike single-objective programming, where there is a feasible strategy that optimizes the objective function, there is no single feasible strategy that simultaneously optimizes all of the objectives when they are in conflict. Rather, for each distance metric (see below), compromise programming provides a Pareto optimal solution, so that there is no other feasible strategy that would improve any objective value without worsening other objective values. There are thus an infinite number of strategies and corresponding objective vectors that are Pareto optimal (Yu 1974; Blasco et al. 1999).

Specification of a preference structure over objectives is an important aspect in the selection of preferred strategies. The usual way is to elicit from decision makers a weighting scheme that reflects their ordering over objectives; in addition to the practical matter of how to elicit such weights, discovering weights is especially difficult when decision makers cannot readily be identified or are unwilling to reveal their preferences (the situation for our case study).[2] As a result, we employ equal weights for each of the objectives but conduct sensitivity analysis with respect to the weighting scheme.

It is much easier to determine potential targets, which is done by finding the respective maximum or minimum value of each objective under single-objective optimization. Regrets are then defined as a measure of the weighted distance between achieved objectives and their targets, with the compromise solution minimizing the overall distance. The problem is that there are different distance metrics according to how much emphasis is placed on "group criteria" versus an individual criterion. While it is possible to determine all of the compromise solutions by varying the balancing parameter (π) between 1 (emphasize "group criteria") and ∞ (focus on a single criterion), as indicated in the next section, our innovation involves the use of fuzzy programming to identify a middle strategy and the decision maker's level of satisfaction with its attainment. This combined compromise-fuzzy programming approach is then applied to the conflicting development objectives of a forest-dependent aboriginal community.

[2] In a government-sponsored study of sustainable forest management, and after five telephone calls to leaders in aboriginal communities, researchers could only get 19 out of 46 communities contacted to respond to a survey (First Nations Forestry Program 2007a, p. 35). Our experience was similar, with aboriginal leaders simply refusing to provide any information on preferences.

Compromise Programming

Compromise programming solves MOP problems by specifying a family of L_π metrics that evaluate distances between points in the objectives space (Yu 1973):

(1)

$$L_\pi(w,x) = \left\{\sum_{q\in Q}[w_q d_q(x)]^\pi\right\}^{1/\pi}, 1 \le \pi \le \infty.$$

Here, $w_q > 0$, $\sum_{q\in Q} w_q = 1$, are weights representing the relative importance of objectives, and $d_q(x) = \frac{f_q^* - f_q(x)}{f_q^* - f_{q*}}$, $q \in Q$, are the normalized distances between the current objective values and the corresponding best (maximum or minimum) values. The current objective value is denoted $f_q(x)$, while f_q^* represents the best possible and f_{q*} the worst possible value of the objective q. While f_q^* is found by single-objective optimization, finding f_{q*} may be difficult as single-objective optimization using the negative of the objective (so as to determine a worst value) may lead to an unbounded solution. Therefore, f_{q*} is often approximated using a suitable lower bound, such as zero when an objective can only take nonnegative values. A solution x to the program

$$(\mathrm{CP}_\pi, w) \quad \min_{x\in F} L_\pi(w,x)$$

is called the weighted *compromise* solution to the MOP problem with respect to w and π.

Ballestero (1997) established a link between the balancing parameter π in compromise programming and a decision maker's risk attitude. A decision maker's attitude toward attainment of multiple objectives is represented by the choice of the distance parameter π ($1 \le \pi \le \infty$): $\pi = 1$ represents an "extremely risk-neutral" decision maker who seeks to realize all criteria (emphasis on "group criteria"), while $\pi = \infty$ represents a decision maker with zero risk tolerance focusing on a single criterion (minimizing the maximum regret). The distance parameter π should not be confused with the Arrow-Pratt coefficient of risk aversion (which relies on some ratio of the first and second derivatives of the utility function with respect to income); risk attitude in the current context should not be confused with its use in expected utility maximization.

For $\pi = 1$, the compromise programming problem becomes:

$$(\mathrm{CP}_1, w) \quad \min_{x \in F} L_1(w, x) = \min_{x \in F} \sum_{q \in Q} w_q d_q(x)$$

and the solution algorithm searches for a strategy to minimize the sum of regrets, or $d_q(x)$. We refer to (CP_1, w) as the compromise *MinSum* program. As π increases, more importance is put on the largest $d_q(x)$. Ultimately, the largest weighted distance completely dominates and, for $\pi = \infty$, becomes:

$$(\mathrm{CP}_\infty, w) \quad \min_{x \in F} L_\infty(w, x) = \min_{x \in F} \max_{q \in Q} w_q d_q(x).$$

Program (CP_∞, w) is not computable, but, if $\lambda = \max_{q \in Q} w_q d_q(x)$, it can be rewritten as (Nakayama 1992):

$$\min \lambda$$

$$(\mathrm{CP}_\infty, w) \ \text{subject to } w_q d_q(x) = w_q \frac{f_q^* - f_q(x)}{f_q^* - f_{q*}} \leq \lambda, q \in Q, \ x \in F$$

(CP_∞, w) is a compromise *MinMax* program that balances the objectives in terms of their normalized distances from the best values.

The metric L_π has an important practical feature for both $\pi = 1$ and $\pi = \infty$: problems (CP_1, w) and (CP_∞, w) are linear programs. This is important given the size and complexity of the forest management problem. However, the linearity assumption is not restricting because solutions for (CP_π, w) $(1<\pi<\infty)$ lie between the solutions for (CP_1, w) and (CP_∞, w).[3] The problem with the L_1 and the L_∞ metrics is that these bounds depend on the decision maker's weights w_q. The difficulty of eliciting a weighting scheme over objectives is further compounded by the need to determine a value for π (recall that π is not a risk aversion coefficient), with any π between 1 and ∞ requiring nonlinear programming to find a solution. To avoid this, fuzzy sets can be used.

Fuzzy Programming

Fuzzy programming facilitates the identification of a middle point between the two boundaries determined by compromise programming, and the likely degree to which one would be satisfied with this strategy. It does so by assuming that objectives and targets are vague and imprecise, and best described in linguistic terms. For example, in our application to a forest-dependent community, the objective "maximize employment" is difficult to measure in an objective sense and might better be described by the fuzzy objective "high employment." In the forestry context, many objectives and targets are vague or imprecisely measured because of uncertainty related to timber growth and yield, natural disturbances (wildfire, pests), market conditions, and unanticipated changes in forest policy and technology.

We quantify imprecise targets using fuzzy numbers (e.g., see van Kooten, Krcmar, and Bulte 2001). Thus, the objective "high financial return" can be represented by the fuzzy number $FN(x)$, whose satisfaction or membership $\mu_{FN(x)}$ is taken to be a nondecreasing linear function:

$$\mu_{FN(x)} = \begin{cases} 1, & \text{if } FN(x) > FN_{\text{Max}} \\ \dfrac{FN(x) - FN_{\text{Min}}}{FN_{\text{Max}} - FN_{\text{Min}}}, & \text{if } FN_{\text{Min}} \leq FN(x) \leq FN_{\text{Max}} \\ 0, & \text{if } FN(x) < FN_{\text{Min}} \end{cases}.$$

It is graphed in figure 1. Complete satisfaction of this objective $(\mu_{FN(x)} = 1)$ occurs when $FN(x)$ is greater than FN_{Max}, while satisfaction is less than 1 $(0 \leq \mu_{FN(x)} < 1)$ when values are below FN_{Max}. There is no satisfaction whatsoever $(\mu_{FN(x)} = 0)$ if $FN(x)$ is lower than FN_{Min}.

The fuzzy objective "high financial return" and the assumed piece-wise linear membership function say something about the decision maker's preferences. For example, the objective "very high financial return" implies the decision maker places even greater weight on financial returns, and the fuzzy membership function would then be nonlinear, as indicated in figure 1.

A second fuzzy objective might be "small deviation in returns," which involves some form of minimization. We can characterize this vague objective by the fuzzy number $DV(x)$ whose membership (satisfaction) $\mu_{DV}(x)$ is represented by a nonincreasing, piece-wise

[3] In the case of two criteria (objectives), it is clear that (CP_1, w) and (CP_∞, w) are bounds for all the solutions for values of π between 1 and ∞ (Freimer and Yu 1976; Yu 1974). Blasco et al. (1999) prove results that guarantee the boundedness of the compromise set under very general conditions when the number of criteria exceeds two. These require the continuity and differentiability of the production-transformation function and existence of absolute maxima for each criterion (Blasco et al. 1999). These conditions hold in our application.

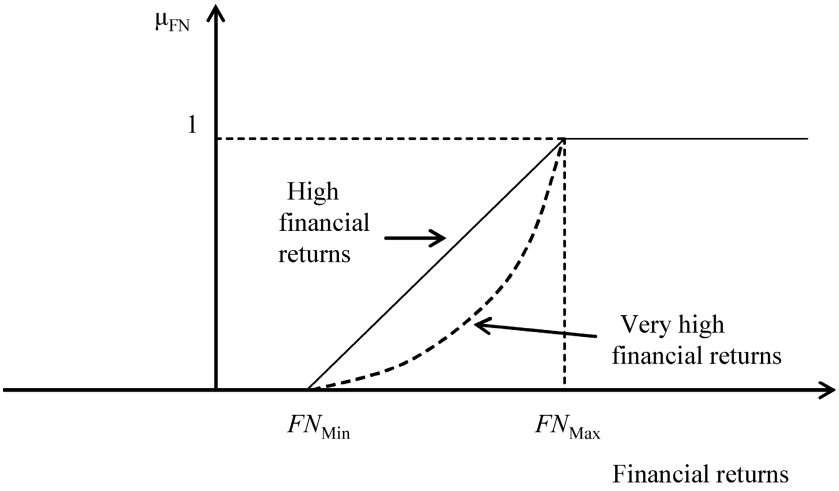

Figure 1. Fuzzy membership functions for objectives: "high financial returns" and "very high financial returns"

linear function:

$$\mu_{DV(x)} = \begin{cases} 1, & \text{if } DV(x) < DV_{\text{Min}} \\ \dfrac{DV_{\text{Max}} - DV(x)}{DV_{\text{Max}} - DV_{\text{Min}}}, & \text{if } DV_{\text{Min}} \leq DV(x) \leq DV_{\text{Max}} \\ 0, & \text{if } DV(x) > DV_{\text{Max}} \end{cases}.$$

Complete satisfaction ($\mu_{DV(x)} = 1$) occurs when $DV(x)$ is less than DV_{Min}, while satisfaction is below 1 when values are greater than DV_{Min}. There is no satisfaction at all ($\mu_{DV(x)} = 0$) when $DV(x)$ is greater than DV_{Max}. The membership functions for "small deviation in returns" and "very small deviation in returns" are provided in figure 2.

The extreme values FN_{Max}, FN_{Min}, DV_{Max}, and DV_{Min} that characterize the respective fuzzy membership functions are determined by solving the (CP_1, w) and (CP_∞, w) problems, and choosing the appropriate MinSum or MinMax value to represent the Max or Min value. For example, $FN_{\text{Max}} = \max\{FN^{\text{MinSum}}, FN^{\text{MinMax}}\}$ while $DV_{\text{Min}} = \min\{DV^{\text{MinSum}}, DV^{\text{MinMax}}\}$.

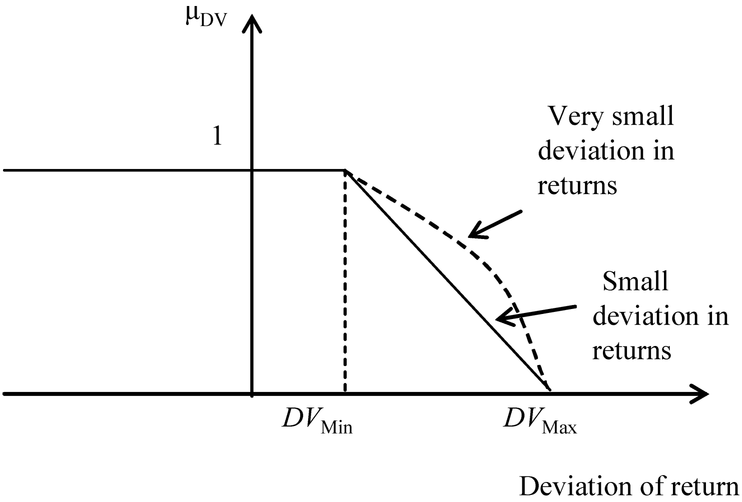

Figure 2. Fuzzy membership functions for objectives: "small deviation in returns" and "very small deviation in returns"

The fuzzy program then selects the strategy that maximizes the minimum satisfaction over the set of feasible strategies (Zimmermann 1978):

$$\max_{x \in F} \min_{q \in Q.} \mu_{q(x)}$$

To implement this, let $\alpha = \min_{q \in Q} \mu_{q(x)} = \min[\mu_{FN(x)}, \mu_{DV(x)}]$ be the overall satisfaction level of a strategy x. The fuzzy strategy x and its satisfaction α are found by solving the linear program:

$$\text{(FP)} \quad \begin{aligned} &\max \alpha \\ &\text{subject to :} \\ &\qquad \mu_{FN(x)} = \frac{FN(x) - FN_{\text{Min}}}{FN_{\text{Max}} - FN_{\text{Min}}} \geq \alpha \\ &\qquad \mu_{DV(x)} = \frac{DV_{\text{Max}} - DV(x)}{DV_{\text{Max}} - DV_{\text{Min}}} \geq \alpha \\ &\qquad x \in F \end{aligned}$$

Application: Economic Development in a Forest-Dependent, Aboriginal Community

The Little Red River Cree Nation (LRRCN) occupies portions of the Lower Peace River region in north-central Alberta, Canada. The forest resources available to the LRRCN are currently the most significant source of potential economic development. In 1986, the Provincial government allocated volume-based quota rights to timber on public lands to the LRRCN, entitling it to an annual volume of softwood and hardwood timber within the tenure area of forest management unit F23 (figure 3); the LRRCN pays stumpage fees to the Province that are keyed to product prices. The LRRCN has its own forest management company that conducts logging and silvicultural activities, while providing training and employment opportunities for aboriginal members. In managing the resources available to it, the aboriginal community needs to balance economic, employment, and timber supply objectives.

The economic criterion consists of net discounted returns to timberland management. Income is important because the LRRCN wishes to invest in up-stream activities, such as wood processing (by purchasing existing processing facilities), and economic diversification more broadly (e.g., guiding and outfitting, oil and gas exploration). Currently, aboriginal people are employed in silviculture (mainly

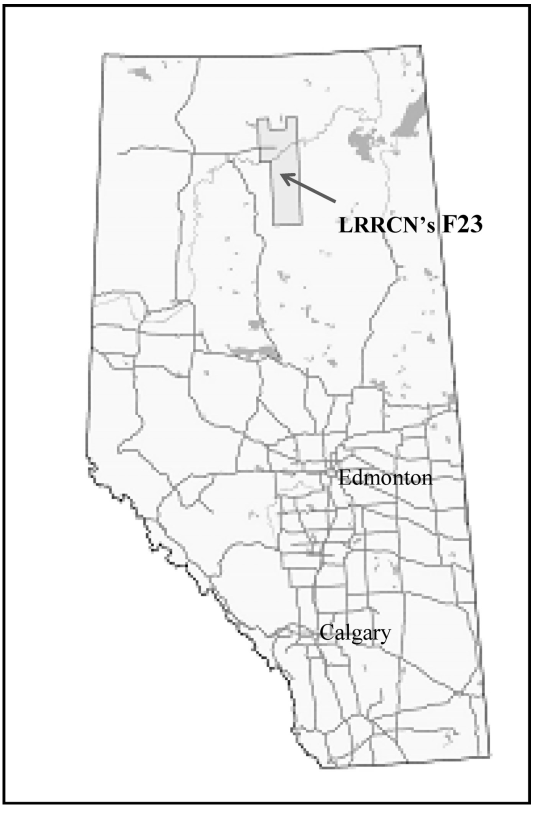

Figure 3. Province of Alberta and study area

tree planting) and logging, but rarely in transportation of logs to mills as this requires significant investment in logging trucks and human capital to run a private business (see First Nations Forestry Program 2007b). Community members are not employed in manufacturing as wood processing mills are located too far away.

To evaluate the employment goal, we use measures of long- and short-term employment. Long-term employment is measured as the cumulative employment in logging and silviculture over the entire time horizon, while the short-term measure constitutes total employment over the early periods (thirty years) of the horizon only. Short-term employment is undoubtedly important for currently unemployed band members (more than half of working age adults are unemployed), but long-term employment is more indicative of a small community's ability to survive on the timber resource base as nonforest economic opportunities gravitate to larger centers.

The timber supply objective addresses concerns related to adequate fiber for mills, and satisfying contractual obligations with the Province and industry. This objective is typically accomplished through even flow of harvest volume over time. We couple even flow to the objective of maximizing cumulative harvest volume over the planning horizon, because this drives fiber supply as high as possible. Even flow carries a further burden as it is used by governments as a rough rule of thumb to address sustained yield (to some extent an ecological objective) and community stability (ensuring employment does not fluctuate over time).

To examine whether local timber resources are adequate to support a sustainable economic base, we formulate long-term strategic forest planning models with a 200-year planning horizon divided into twenty decades and chosen according to the strategic planning practices used in Canada to ensure that sustainability conditions are truly satisfied. The dynamic character of our model takes into account the effect that current decisions have on the future state of the forest and available future management options.

Harvest scheduling decisions are taken to be nonspatial to keep the programming problem manageable. Forest attributes are aggregated into management strata, where a stratum m is defined as a combination of tree species, stand density, height, and age. Let M denote the set of management strata, T the number of planning periods, and $TS < T$ the number of periods considered for short-term employment. A decision variable $x = x_{mt}$ represents the area (hectares) of stratum m harvested in period t. Denote the merchantable volume from a hectare of stratum m harvested in period t by v_{mt}, the net revenue per hectare of stratum m in period t by nv_{mt}, and employment generated by harvesting a hectare of stratum m in period t by e_{mt}. Finally, let r be the discount rate. The objective functions can then be stated as:

Discounted net revenue from timber:

$$N(x) = \sum_{m \in M} \sum_{t=1}^{T} (1+r)^{-t \times 10} nv_{mt} x_{mt}$$

Cumulative volume:

$$V(x) = \sum_{m \in M} \sum_{t=1}^{T} v_{mt} x_{mt}$$

Long-term employment:

$$EL(x) = \sum_{m \in M} \sum_{t=1}^{T} e_{mt} x_{mt}$$

Short-term employment:

$$ES(x) = \sum_{m \in M} \sum_{t=1}^{TS} e_{mt} x_{mt}$$

Maximum harvest flow deviation:

$$D(x) = \max_{t} |Vol_{t+1}(x) - Vol_t(x)|.$$

where $Vol_t(x) = \sum_{m \in M} v_{mt} x_{mt}$ is the volume harvested in period t. Here, $D(x)$ is the maximum absolute difference between harvest volumes in subsequent periods. In the case of even flow, this difference is zero; in all other management strategies, it reflects the level of variations in timber supply over time. If stability of timber supply is a management goal that aims to ensure community stability, $D(x)$ is to be minimized.

The multiple-objective programming model can then be written as:

(N) Max $N(x)$
(V) Max $V(x)$
(EL) Max $EL(x)$
(ES) Max $ES(x)$
(D) Min $D(x)$
subject to $x \in F$.

The feasible set F consists of all the technical constraints on land availability, forest management, and silvicultural options, the initial and terminal timber inventories, and the nonnegativity constraints (discussed below). For the subsequent fuzzy programming model, fuzzy membership functions are constructed as discussed above. All models constitute a series of linear programs coded in GAMS and solved using the CPLEX solver (Brooke et al. 1998).

To incorporate the LRRCN's requirement that forest management be compatible with traditional land use and cultural values, certain forestlands are excluded from the harvest land base; commercial logging is prohibited on the community's reserve land, protected areas, special places, natural areas, and areas with specific wildlife habitat characteristics. Also excluded are forest areas where stands are inoperable or isolated, or where operating ground rules require exclusion. The timber harvesting land base covers 305,918 hectares divided into thirteen classes for which timber inventory and yield data were available (Timberline Forest Inventory Consultants Ltd. 2001a, 2001b). The forest resources are made

Table 1. Output Generated by Employment in Various Forest Management Activities[a]

Logging	Output	Planting & Silviculture	Output
Felling	50 m^3/hr	Tree planting	0.1 ha/hr
Skidding	48 m^3/hr	Stand tending	0.1 ha/hr
Delimbing	46 m^3/hr	Site preparation	1.0 ha/hr
Loading	100 m^3/hr		

[a]Includes employment in all categories: operators, administration, and supervision.
[b]Assumes 2000 trees per ha.

up of two predominant species—white spruce and aspen. The spruce-dominated stands are typically reforested to conifers after harvest, while aspen-dominated stands are left to regenerate on their own to deciduous species. Average harvest costs are \$32 per cubic meter for softwoods (including trucking and artificial regeneration) and \$18/m^3 for hardwoods (including trucking but with natural regeneration). To ensure sustainability and meet ecological constraints at end of period, we require that 10% of the ending deciduous and conferous inventories be greater than 100 years old.

Information about the prices LRRCN negotiated with the forest industry is confidential. For the current analyses, therefore, we use estimates of softwood and hardwood sawlog prices from the British Columbia Interior Log Market (BC Ministry of Forest and Range 2006). Our estimated prices are \$50/m^3 for conifer logs and \$30/m^3 for hardwood logs; a 5% real rate of discount was used. We also examine the sensitivity of results to changes in prices and discount rate. To convert forestry activities into employment, we use the values indicated in table 1.

Basic Strategies: Single-Objective Optimization Results

The MOP model is first solved for each of the objectives separately with all constraints that define the feasible set F in place. That is, we optimize each objective function individually over the set of feasible strategies F to determine f_q^* for all $q \in Q$ and compute the values of the remaining criteria at those optimal strategies. We refer to these outcomes as the ideal objective values; they are provided in the pay-off matrix (table 2) along the main diagonal and indicated in bold. Each row of table 2 consists of values of the individual objectives calculated for the corresponding basic strategy. The first two objectives are to maximize the net present value and the cumulative harvest volume over the planning horizon, followed by the objectives of maximizing the long-term (cumulative 200-year) and short-term (first thirty years) employment. The last is to minimize the maximum deviation between period harvests; this strategy (denoted D) is obtained by maximizing the cumulative volume $V(x)$ under even-flow constraints for both the softwood and hardwood harvest, thus providing the highest possible even-flow harvests over the horizon. Note that the sustained-yield strategy represented by this final row coincides with current forest management practice in the study area.

From table 2, it is clear that all objectives are in conflict. In addition to the conflict between high net present value and cumulative harvest volume, the results indicate significant tradeoffs among other objectives. For example, in order to attain the maximum net present value of \$474.7 million, cumulative volume drops to 125.9 million m^3 while at the same time

Table 2. Payoff Matrix for Basic Scenario Strategies[a]

Objective Values When Single Objective on Right is Optimized	Objective That is Optimized				
	N	V	EL	ES	D
NPV (10^6 \$)	**474.683**	373.588	365.649	303.353	194.203
Volume (10^6 m^3)	125.949	**154.835**	154.565	123.999	132.128
Long-term employment (10^6 hrs)[b]	17.018	18.693	**19.117**	14.837	15.795
	(48.62)	(53.41)	**(54.62)**	(42.39)	(45.13)
Short-term employment (10^6 hrs)[b]	5.472	5.034	5.357	**6.139**	2.258
	(104.23)	(95.89)	(102.04)	**(116.92)**	(43.01)
Max flow deviation (10^6 m^3)	17.836	26.588	25.779	27.103	**0.000**

[a]Figures in bold along the main diagonal denote ideal values obtained by single-objective optimization of the objective on the left. The worst values of each objective in the payoff matrix are underlined, although, unlike the ideal values along the diagonal, there is no guarantee that these are the worst values. Thus, the ideal vector is $f^* = \{474.683, 154.835, 19.117, 6.139, 0\}$, but we choose the 'nadir' vector as $f_* = \{0, 0, 0, 0, 27.103\}$.
[b]Full-time equivalent (FTE) permanent jobs are provided in parentheses. Long-term jobs are obtained by dividing total long-term hours by 1,750 hours per year × 200 years (length of planning horizon); short-term jobs are obtained by dividing total short-term hours by 1,750 × 30 years.

harvests deviate up to 17.8 million m^3 between consecutive periods. The strategy of maximizing short-term employment leads to the worst values for cumulative volume and long-term employment, plus it generates the greatest deviation of harvest. In order to generate 6.1 million hours of employment (or some 117 permanent, full-time jobs) over the first three periods, cumulative volume drops to 124.0 million m^3 relative to its ideal value of 154.8 million m^3, long-term employment falls to its lowest value of 14.8 million hours (42 jobs), and there is a difference of 27.1 million m^3 between consecutive period harvests.

The trade-off required with respect to the even-flow objective is achievable only at huge financial cost and significant loss in short- and also long-term employment, as well as sacrifice in cumulative harvest volume. The cost of the even-flow strategy calculated relative to the ideal net present value is \$280.5 million (59% below ideal), while respective short- and long-term employment are reduced by 74 and 9.5 permanent full-time jobs (63% and 17% below ideal), and the sacrifice in cumulative volume amounts to 22.7 million m^3 (15% less).

Compromise Strategies

Since none of the management strategies that optimize a single objective function is acceptable, we seek a resolution to the conflict by solving the (CP_π, w) program for $\pi = 1$ and $\pi = \infty$. The distance measure in equation (1) requires identification of the worst and best possible values of each objective q. For this application, the ideal vector is $f^* = \{474.683, 154.835, 19.117, 6.139, 0\}$, obtained directly from single-objective optimization (table 2). However, as noted earlier, finding an appropriate nadir vector f_{q*} may be troublesome, so it is usually approximated by a suitable lower bound. For the nonnegative objective functions $f_q(x)$, $q \in \{N, V, EL, ES\}$, the nadir vector is not identical to the underlined values in table 2; hence, it is chosen as $f_* = \{0, 0, 0, 0, 27.120\}$—the worst possible values of the objectives. Outcomes of the compromise programming MinSum and MinMax management strategies are provided in table 3 along with the corresponding distance measures. Sensitivity results for various objective weighting schemes, output prices, and discount rates are also provided. Note that the f_N^* value (ideal or target value for discounted net revenue) will vary with discount rate and prices, but the ideal values for the other objectives will remain the same, as will all the nadir values.

Consider first the baseline strategy with equal weights, 5% discount rate, and stumpage values of \$30/m^3 for hardwoods (deciduous trees) and \$50/m^3 for softwoods (conifers). The normalized overall distance (objective) values are 0.106 for the L_1 metric (MinSum strategy) and 0.056 for the associated L_∞ metric (MinMax strategy), indicating that the overall normalized distance between realized objectives and targets is relatively small, particularly for MinMax. For the MinSum strategy net present value is 77.4% of its best possible value, while long-term employment attains 94.3% of its ideal; the outcomes of the MinMax strategy range between 71.9% and 97.3% of ideal. Given the lower objective value for MinMax (recall the objective is minimization), the MinSum strategy seems to be better balanced with four of five objectives within 12% of ideal (and three within 7.5% of ideal). For the MinMax strategy, four objectives are more than 20% from their ideal, while deviation of timber flow is very close to its target. With the exception of the low-price scenario, a similar pattern (but with different magnitudes for deviations) emerges in comparing the MinSum and MinMax strategies. Yet, there is no unequivocal way to determine which is preferred.

Compared to the even-flow strategy required under Alberta's extant forest management practices, financial performance and short-term employment prospects could be enhanced with only a slight relaxation of the even-flow constraint and little or no worsening of the cumulative volume and long-run employment objectives (compare table 3 results with those in the last column of table 2).

Fuzzy Strategy

The crisp objectives of single-objective and compromise programming are respecified as fuzzy objectives to reflect their vagueness and the imprecision with which they are measured. Thus, the objective Max $N(x)$ becomes the objective "high discounted net returns"; Max $V(x)$ becomes "high timber output"; Max $EL(x)$ and Max $ES(x)$ become "high long-run (short-run) employment"; and Min D(x) becomes "low maximum deviation from even flow." To construct membership functions for each of these fuzzy objectives, it is first necessary to define the ranges of acceptable objective values. As noted earlier, we use the outcomes from the two extreme

Table 3. Compromise Programming Results, Various Scenarios[a]

Objectives	MinSum	MinMax	MinSum	MinMax	MinSum	MinMax
Weighting Scheme	Equal Weights		(0.3, 0.1, 0.1, 0.1, 0.4)		(0.1, 0.3, 0.3, 0.2, 0.1)	
NPV (10^6 \$)	367.481	341.350	378.708	109.879	388.822	230.108
	[0.226]	[0.281]	[0.202]	[0.769]	[0.181]	[0.515]
Volume (10^6 m^3)	143.442	111.344	142.688	111.490	140.311	125.853
	[0.074]	[0.281]	[0.078]	[0.280]	[0.094]	[0.187]
Long-term FTE jobs[b]	51.52	43.05	51.91	36.23	50.92	43.92
	[0.057]	[0.212]	[0.050]	[0.337]	[0.068]	[0.196]
Short-term FTE jobs[b]	103.10	86.90	105.49	17.18	105.16	53.34
	[0.118]	[0.257]	[0.098]	[0.853]	[0.101]	[0.544]
Max flow dev (10^6 m^3)	2.887	1.353	2.924	1.627	2.690	0.226
	[0.058]	[0.027]	[0.058]	[0.033]	[0.054]	[0.005]
Value of L_1 or L_∞[c]	[0.106]	[0.056]	[0.082]	[0.086]	[0.109]	[0.155]
Discount Rate	3%		5%		10%	
NPV (10^6 \$)	506.367	528.275	367.481	341.350	293.558	49.679
	[0.130]	[0.093]	[0.226]	[0.281]	[0.168]	[0.859]
Volume (10^6 m^3)	146.476	140.477	143.442	111.344	145.361	64.993
	[0.054]	[0.093]	[0.074]	[0.281]	[0.061]	[0.580]
Long-term FTE jobs[b]	52.60	49.56	51.52	43.05	52.71	24.69
	[0.037]	[0.093]	[0.057]	[0.212]	[0.035]	[0.548]
Short-term FTE jobs[b]	104.03	107.48	103.10	86.90	107.94	23.85
	[0.110]	[0.081]	[0.118]	[0.257]	[0.077]	[0.796]
Max flow dev (10^6 m^3)	3.219	3.441	2.887	1.353	5.192	0.000
	[0.064]	[0.069]	[0.058]	[0.027]	[0.104]	[0.000]
Value of L_1 or L_∞[c]	[0.079]	[0.019]	[0.106]	[0.056]	[0.089]	[0.172]
Price Sensitivity	d = \$20/m^3; c = \$35/m^3		d = \$30/m^3; c = \$50/m^3		d = \$60/m^3; c = \$100/m^3	
NPV (10^6 \$)	31.938	39.198	367.481	341.350	605.829	605.829
	[0.159]	[0.341]	[0.226]	[0.281]	[0.000]	[0.000]
Volume (10^6 m^3)	130.231	102.035	143.442	111.344	126.256	77.267
	[0.596]	[0.505]	[0.074]	[0.281]	[0.185]	[0.501]
Long-term FTE jobs[b]	46.15	33.74	51.52	43.05	47.16	32.16
	[0.155]	[0.382]	[0.057]	[0.212]	[0.137]	[0.411]
Short-term FTE jobs[b]	56.34	57.60	103.10	86.90	60.71	58.35
	[0.518]	[0.507]	[0.118]	[0.257]	[0.481]	[0.501]
Max flow dev (10^6 m^3)	0.000	0.471	2.887	1.353	1.767	0.923
	[0.000]	[0.009]	[0.058]	[0.027]	[0.035]	[0.018]
Value of L_1 or L_∞[c]	[0.286]	[0.136]	[0.106]	[0.056]	[0.167]	[0.100]

[a]The MinSum values represent the solution of the (CP_1, w) program, while MinMax values represent the solution to the (CP_∞, w) program. Values of the normalized distances are provided in square brackets. The baseline scenario is equal weights, discount rate of 5%, and stumpage values of \$30/m^3 and \$50/m^3 for deciduous (d) and coniferous (c) timber, respectively.

[b]FTE refers to full-time equivalent permanent jobs. See footnote b, table 2.

[c]The L_1 metric is associated with MinSum, L_∞ with MinMax.

[d]The NPV target changes with discount rates and prices, but other ideal values remain the same. For discount rates, NPV*(3%) = \$582.270 mil and NPV*(10%) = \$352.930 mil; for higher prices NPV* = \$605.829 mil; for lower prices NPV* = \$79.114 mil.

compromise strategies to define the ranges of acceptable outcomes in the fuzzy targets.[4] Membership functions for the fuzzified objectives N, V, EL, and ES are similar to those of figure 1, while that of objective D is similar to figure 2, with the values from table 3 (and identified in table 4) constituting the extreme values at which the (assumed) linear fuzzy membership functions become 0 (no membership in the set) or 1 (compete membership).

The outcomes of the fuzzy strategy obtained by solving (FP) are provided in table 4. The fuzzy outcomes fall between the MinSum and MinMax compromise outcomes. One

[4] In contrast, instead of the compromise results, Duval and Featherstone (2002) used the best value of an objective (obtained by optimizing the single objective) and the worst possible value. We provide some sensitivity of methods for selecting best and worst values.

Table 4. Outcomes of the Fuzzy Strategies

Item	From Basic Scenario		Over All Scenarios	
Fuzzy Membership Parameters				
$\{N_{\text{Min}}, N_{\text{Max}}\}$ (10^6 \$)	{108.334, 367.481}		{31.938, 605.829}	
$\{V_{\text{Min}}, V_{\text{Max}}\}$ (10^6 m^3)	{69.323, 143.442}		{64.993, 146.476}	
$\{EL_{\text{Min}}, EL_{\text{Max}}\}$ (FTE jobs)	{27.72, 51.52}		{24.69, 52.71}	
$(ES_{\text{Min}}, ES_{\text{Max}}\}$ (FTE jobs)	{27.38, 103.10}		{23.85, 107.94}	
$(D_{\text{Min}}, D_{\text{Max}}\}$ (10^6 m^3)	(0.000, 2.887)		(0.000, 5.192)	
Objective	Outcome	Degree of Membership[a]	Outcome	Degree of Membership[a]
NPV (10^6 \$)	303.24	<u>0.752</u>	379.04	<u>0.605</u>
Volume (10^6 m^3)	141.68	0.976	142.90	0.969
Long-term FTE jobs	48.27	0.863	51.31	0.950
Short-term FTE jobs	84.33	<u>0.752</u>	96.61	0.875
Max flow deviation (10^6 m^3)	0.72	<u>0.752</u>	2.05	<u>0.605</u>

[a] Interpreted as level of satisfaction with attainment of the objective. Minimum value of the fuzzy program's objective value (minimum value of α) is underlined.

advantage of the fuzzy approach is that it gives some indication of the level of satisfaction that a decision maker (LRRCN community) might attach to the attainment of various objectives. The fuzzy strategy is the only one that provides a true compromise solution to the MOP problem for LRRCN economic development. This compromise feature is supported by a distribution of membership values for the different objectives (table 4). The membership values range from 0.752 for the net present value, short-term employment and flow deviation objectives to 0.976 for the cumulative volume objective. We interpret this as follows: The degree of satisfaction or comfort that the decision maker has in implementing the strategy obtained by solving the fuzzy program is at least 0.752. When the values used to determine the fuzzy membership functions increase, the comfort level declines as indicated in columns 3 and 4 of table 4. Thus, a decision maker should be more comfortable with fuzzy results based on membership functions derived from compromise programming that those derived from the single-objective optimization results. This does not imply that the former strategy is better in some objective sense; it only suggests that the decision maker feels better about the way the outcomes satisfy all of the objectives.

Finally, in table 5 outcomes of the MinSum, MinMax and fuzzy strategies are compared with each other and with the current even-flow policy (D) on the basis of their relative performance with regard to the ideal values. What is particularly striking is that the outcomes associated with the compromise programming and fuzzy programming solutions are strikingly different from the current even-flow policy. The results indicate that there are large gains to be made to the other objectives from relaxing the even-flow constraint, but that further gains likely involve difficult trade-offs among all objectives with the basic fuzzy strategy representing the best compromise for the base-case scenario. Further evidence of the problems associated with various strategies and implied trade-offs can be obtained by analyzing temporal harvests.

Table 5. Even-flow, Compromise and Fuzzy Outcomes Relative to Single-Objective Ideals

Objective	Current Even-flow	Compromise		Fuzzy	
		MinSum	MinMax	Basic	All
NPV (10^6 \$)	40.9%	77.4%	71.9%	63.9%	79.8%
Volume (10^6 m^3)	85.3%	92.6%	71.9%	91.5%	92.3%
Long-term FTE jobs	82.6%	94.3%	78.8%	88.4%	93.9%
Short-term FTE jobs	36.8%	88.2%	74.3%	72.1%	82.6%
Max. flow dev. (10^6 m^3)	100.0%	94.2%	97.3%	97.3%	92.4%

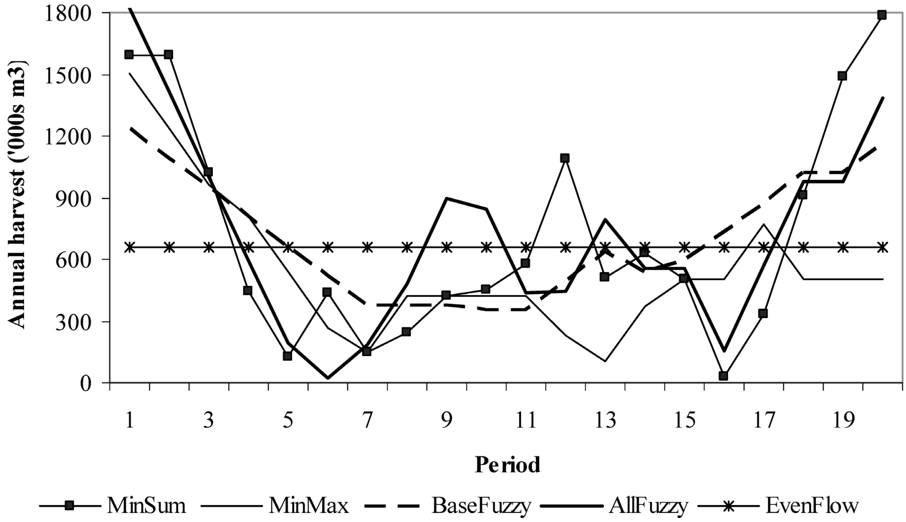

Figure 4. Annual harvest over the horizon for the alternative strategies

Harvest Flow

When we consider annual harvests per decade under the assumption that decision makers focus only on a single objective, we find that harvests will be constant over time (minimize deviation of harvests between decades), take place almost entirely in the first thirty years of the planning horizon (maximize short-term employment), or take on a significant temporal fluctuating pattern (other objectives). In all cases except even flow, harvests are projected to cease for a significant period beginning as early as the third decade. Cessation of harvests is avoided in the even-flow case only because harvest levels are depressingly low from an economic development point of view. Can a compromise or fuzzy strategy lead to outcomes that avoid this possibility?

Harvest levels for the even-flow, compromise and fuzzy strategies are provided in figure 4. The good news is that, even though harvest levels in each of the first decades are declining, the compromise and fuzzy strategies are able to delay total cessation of harvests to at least the fifth decade, while maintaining harvest levels above that under the current even-flow regime for at least thirty years.[5] This suggests that, while a downfall in timber harvests is unavoidable, harvest levels might be sufficiently high so that they could be relied upon as a driver of economic development for perhaps twenty to thirty years, after which the local economy must be diversified if the forest-dependent community is to survive. This conclusion is reinforced by the projections concerning employment.

Discussion and Conclusions

Finding an acceptable solution to the multiple-objective programming problem using outcomes of compromise programming is not a completely novel idea. The novelty introduced here is that we employ the extreme bounds from compromise programming to construct fuzzy membership functions for more than two objectives, with fuzzy programming then used to identify a middle ground strategy and the level to which a decision maker might be satisfied with such a strategy. This has several advantages compared to other methods of multiple-objective decision making. First, using fuzzy programming we are able to determine a strategy whose outcome lies between the two extremes represented by the MinSum (risk neutral) and MinMax (risk aversion) strategies of compromise programming. Second, using the MinSum and MinMax solutions to construct the fuzzy membership functions leads to a higher level of decision maker comfort (satisfaction) with the final outcome than if fuzzy memberships were constructed using the results from single-objective optimization. Third, our approach explicitly takes into account two extreme attitudes with respect to

[5] Higher harvests in the final two decades under both fuzzy strategies and, especially, the MinSum strategy are driven primarily by the volume objective. This occurs because, as noted earlier, the end point constraint is in terms of an old-growth requirement.

risk aversion—risk neutrality as represented by the L_1 metric and total risk aversion as represented by the L_∞ metric. Finally, the approach does not require information about decision makers' risk preferences.

Although we do not require information on risk preference, it may still be desirable to elicit a decision maker's preferences regarding the relative importance of objectives. In the case study, we did so using sensitivity analysis with respect to the weighting scheme. We also suggested how we might employ linquistic information about decision makers' preferences over objectives within a fuzzy framework, although we did not consider this approach in our study as it would require us to abandon the linear programming framework (viz., nonlinear fuzzy membership functions). Future research might compare crisp weights with fuzzy ones—a comparison of the elicitation of a traditional weighting scheme over preferences with linguistic responses leading to fuzzy numbers as illustrated in figures 1 and 2. In addition to examining the ease with which to elicit information, results from multi-attribute utility optimization and compromise programming could be compared with fuzzy programming.

A major reason for undertaking the current research was to investigate the types of trade-offs that forest-dependent, aboriginal communities in northern Canada face. This is particularly relevant when forest management policy focuses on a single objective, an even flow of timber, which is the bedrock of public forest policy in Canada. This objective is meant to maintain employment at a relatively constant level thereby enabling community stability if not economic growth and development. Our results indicate that the even-flow policy is an insufficient driver of economic development in timber-dependent communities; it is not adequate for meeting employment objectives and, based on low timber output, cannot be used to generate secondary manufacturing jobs. The dilemma of even-flow constraints for forest-dependent communities is compounded by the fact that, in order to remain globally competitive, the number of jobs per unit of harvest will fall over time due to mechanization, technological improvements and economies of size. Perhaps this is why Leake, Adamowicz, and Boxall (2006) found that forest dependence was an obstacle to the economic development of rural communities in Canada.

By including multiple objectives and uncertainty explicitly into forest management models, we identified a variety of alternative strategies that provide significantly different levels of projected timber supply, economic performance and employment. In particular, management strategies that allow for some flexibility in the even-flow constraint produced much higher economic benefits as well as greater employment opportunities. While the even-yield strategy guarantees nondeclining employment opportunities over the planning horizon, mainly because it provides jobs in silviculture (which is labor intensive), the strategy is unacceptable for addressing the employment concerns of a growing community population. To do so requires higher financial returns to provide economic surpluses that can be used to fund economic development and diversification. Strategies that rely on intensive harvesting early in the planning horizon may enable forest-dependent communities to achieve high financial returns without sacrificing the future use of forest resources, although a period of low or zero harvests must be accepted. Without it, economic development that is already difficult to achieve may not be realized at all.

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