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Multiple objective forest land management planning: An illustration

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Abstract: Multiple Objective Programming (MOP) has undergone a rapid period of development during the last decade. Concurrently, increased land-use pressures have stimulated forest land management analysts to develop and utilize more sophisticated planning aids to address complex multi-resource issues involving multiple objectives and decision makers.

To illustrate the potential use of MOP in land management planning, a demonstrative example is examined using an interactive technique—the STEM method. This method was chosen because of its promise as a rational, practical and systematic means of exploring feasible alternative solutions to multiple objective forest land management problems.

Introduction

Multiple Objective Programming (MOP) is concerned with planning problems in which several conflicting objectives are to be optimized simultaneously. Multiple use forest planning exemplifies this situation because most forest land use planning problems involve a consideration of multiple conflicting goals and objectives such as: increased net revenue from timber resources, improved water quality, protection of wildlife, preservation of natural beauty, and increased recreational opportunities. The satisfactory attainment of these objectives is a major concern in forest land management planning. Examining the applicability of MOP as a planning tool for forest land management planning is the primary motivation of this paper.

The application of mathematical programming to forest land management planning has been limited mainly to linear programming (LP) and goal programming (GP) (Bare et al., 1984; Harrison and de Kluyver, 1984). Despite the fact that multiple use has been recognized, and regarded by some as an operational concept for almost two decades (Hartgraves, 1979), land use analysts have only recently begun to develop planning models capable of adequately handling multiple objectives. To date, most of the literature dealing with methodologies for multiple objective forest land management planning is based on the use of GP (Bare and Anholt, 1976; Bell, 1975; Bell, 1976; Dane, Meador and White, 1977; Dress, 1975; Dress and Field, 1979; Field, 1973; Field, Dress and Fortson, 1980; Rustagi, 1976; Schuler and Meadows, 1975; Schuler, Webster and Meadows, 1977; Hotvedt, Leuschner and Buhyoff, 1982; Arp and Lavigne, 1982; Mendoza, 1986; and Walker, 1986). Recently, however, questions concerning the ability of GP to capture the vital characteristics and elements of forest land management planning have been raised. The most intriguing of these questions are those described by Cohon and Marks (1975), Dyer et al. (1979), Hrubes and Rensi (1981), and Zeleny (1981). The implications of these questions are discussed later in this paper.

Other MOP techniques have been used sparingly in forestry. A few notable exceptions include Bertier and de Montgolfier (1974), Steuer and Schuler (1978), Mattheis and Land (1984), de

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Kluyver, Daellenbach and Whyte (1980), Allen (1986), and Harrison and Rosenthal (1986).

During the last decade, there have been a great number of MOP techniques developed. A comprehensive review of these techniques can be found in a number of sources including those of Evans (1984), Raff and Zeleny (1980), Hwang et al. (1980), and Zionts (1978). Additionally, many textbooks cover the subject in great detail (Cohon, 1978; Chankong and Haimes, 1983; Zeleny, 1982). In this paper, an example of one technique—the STEM method—is included to illustrate the potential use of MOP in forest land management planning.

Mathematical background

The general MOP problem involving p objectives ($p \geqslant 2$), n decision variables and m constraints can be expressed as:

$$\text{Max } Z(X) = [Z_k(X), \text{ for } k = 1, 2, \ldots, p], \quad (1)$$

$$\text{subject to} \quad g_h(X) \lesseqqgtr b_h, \quad \text{for } h = 1, 2, \ldots, m, \quad X \geqslant 0, \quad (2)$$

where Z is a vector valued function consisting of the objective functions $Z_k(X)$, for $k = 1, 2, \ldots, p$ and X is a vector consisting of decision variables $X_1, X_2, \ldots, X_n$. If $Z_k(X)$ and $g_h(X)$ for all $h = 1, 2, \ldots, m$, and $k = 1, 2, \ldots, p$ are linear, the multiobjective problem is referred to as a multiobjective linear program (MOLP). The STEM method illustrated in this paper is an example of a MOLP technique.

The concept of an optimal solution as used in classical single objective optimization has a nebulous meaning in MOP. In general, a vector such as Z in (1) cannot be optimized except for the trivial case where an 'ideal solution' exists (i.e. all objectives are complementary and can be optimized simultaneously). Hence, in MOP a different conceptual view of optimization is required.

To approach this formally, all feasible solutions to (1) and (2) are classified into two mutually exclusive sets: (a) nondominated/noninferior/efficient, or pareto-optimal solutions for (b) dominated/inferior/inefficient solutions [1].

Clearly, a decision maker would like to select a nondominated solution as the preferred choice. However, in the presence of multiple and competing objectives there will be many nondominated candidates to select from. In the absence of a utility function which expresses preferences over the entire set of nondominated solutions, the decision maker will be unable to select an 'optimal' solution. Instead the decision maker must articulate a set of preferences for the various objective functions by implicitly or explicitly weighting each objective. The preferred nondominated solution is labelled the 'best compromise' solution reflecting the fact that 'best' is dependent upon the articulated preferences.

Multiobjective programming methods

MOP techniques may be classified as: (a) generating techniques, (b) noninteractive methods requiring the prior articulation of preferences, (c) interactive methods relying on the progressive articulation of preferences, and (d) techniques designed to generate new solutions, not just to evaluate previously specified solutions as in (a). Although not mutually exclusive, these four categories embrace the major MOP techniques used to day.

Generating techniques refer to those approaches whereby the analyst generates the entire set of nondominated solutions to a predefined problem in the absence of any goal preference information from the decision maker. Given this set of solutions, the decision maker applies some preference structure to arrive at the best compromise. Noninteractive techniques require that the decision maker articulate preferences among objectives prior to the analysis. These methods avoid generating the entire nondominated solution set, but require considerable 'a priori' information concerning preferences.

Interactive approaches are characterized by

[1] A dominated solution is defined as: A feasible solution $X^1 = (X_1, X_2, \ldots, X_n)$ and any other feasible solution $X^2 = (X_1, X_2, \ldots, X_n)$ can be represented in terms of the values over their objective functions as: $Z(X^1) = (Z_1(X^1), Z_2(X^1), \ldots, Z_p(X^1)]$ and $Z(X^2) = [Z_1(X^2), Z_2(X^2), \ldots, Z_p(X^2)]$. X^1 is said to be dominated by X^2 if and only if $Z_k(X^1) \leqslant Z_k(X^2)$ for $k = 1, 2, \ldots, p$ and $Z_k(X^1) < Z_k(X^2)$ for at least one k.

three basic iterative steps: (a) solve the MOP problem based on some initial set of preferences to obtain a feasible, preferably nondominated, solution, (b) have the decision maker react to this solution, and (c) use the decision maker's response to formulate a new set of preferences, resulting in a new problem to be solved. Because of its appeal as a planning and decision making tool, some of the newer generating techniques have adopted this approach in an attempt to reduce the set of nondominated solutions presented to the decision maker for evaluation.

Many real-world problems are too complex to permit all objectives to be captured within a mathematical programming model (Liebman, 1976). This is because some issues are qualitative in nature, unknown, or unrevealed by decision makers (Brill, 1979). Hence, while the MOP techniques previously presented may be useful for solving certain classes of problems, it may be important to generate and examine additional solutions if there are important unmodeled issues. Furthermore, in typical cases, there are numerous mathematical solutions that are nearly equal with respect to modeled objectives, but which differ considerably from each other in decision space. To be useful for solving these types of complex problems, MOP methods which generate additional solutions, and not just evaluate predefined solutions, may be needed (Brill, Chang and Hopkins, 1982 and Chang and Brill, 1982).

The STEM method

In the illustrated example which follows, the STEM method is applied to a forest land management planning problem. Among the interactive approaches, the STEM method is applicable to forest land management planning because it can computationally accommodate problems of the size encountered and is easy to understand. Further, it uses the highly efficient simplex which is familiar to forest planners. This interactive MOLP method seeks to identify the best compromise solution by presenting sequential compromise solutions to the decision maker with each reflecting the decision maker's preferences (Benayoun et al., 1971). This is untuitively appealing as it clearly shows that compromises must be made between different objective functions if the best compromise solution is to be identified. However, an explicit calculation of trade-offs between objective functions is not provided as part of STEM.

The STEM method begins with the construction of a pay-off table which is found by solving (1)–(2) sequentially for each of the p objective functions. For the k-th objective we obtain a solution (X^k) which maximizes Z_k. This maximum value is labelled M_k. The values of the remaining $p-1$ objectives are then evaluated at X^k. These values are used to fill out the k-th row of the pay-off table. The diagonal elements represent the ideal solution (usually infeasible) where the maximum value of each objective is realized. Following this, the STEM method consists of a calculation and a decision making phase.

Initiating the calculation phase, the STEM algorithm seeks to find a compromise solution which is 'nearest' to the ideal solution. [2] This is accomplished by minimizing the difference (D) between the p objective function values and their respective maximum values M_k. This involves solving the LP problem:

$$\text{Minimize} \quad D, \tag{3}$$

$$\text{subject to} \quad D \geqslant w_k[M_k - Z_k(X)] \quad \text{for } k = 1, 2, \ldots, p, \tag{4}$$

$$X \in F^i \text{ and } D \geqslant 0. \tag{5}$$

Constraint (4) ensures that D is no smaller than each weighted (w_k) difference between the maximum value and the actual value of each objective. Initially, (for $i=0$), F^0 in (5) is defined by the feasible region described in (2). For succeeding iterations, F^{i+1} is modified from the previous feasible region F^i. This modified feasible region incorporates the decision makers reactions to the solution found at the previous iteration and is defined below in (8)–(9).

The weights (w_k) in (4) indicate the relative magnitude of the deviations from the ideal solution for each objective. Three options exist for specifying these weights: (a) all w_k may be set equal, (b) any set of weights selected by the deci-

[2] The STEM method uses a weighted minimum distance metric to define the best compromise solution. Specifically, an infinite distance metric (D) defined as $D = \max_{k=1,2,\ldots,p}[M_k - Z_k(X)]$ is minimized. This is equivalent to assigning an infinite weight to the objective with the greatest shortfall from its maximum value M_k. Weights, as shown in (4), modify this metric.

sion maker may be used, or (c) the following formula approach may be adopted:

$$w_k = \alpha_k / \sum_k \alpha_k \tag{6}$$

where

$$\alpha_k = \underbrace{\frac{M_k - m_k}{M_k}}_{\text{Term 1}} \cdot \underbrace{\left[\sum_j (c_{kj})^2\right]^{-1/2}}_{\text{Term 2}} \tag{7}$$

in which m_k is the minimum value of the k-th objective found by finding the smallest cell in the k-th column of the pay-off table and c_{kj} is the coefficient for the j-th decision variable in the k-th objective function.

"The weights are used to capture the relative variation in the value of the objectives and to suppress the inordinate weight one objective may receive by virtue of its scale" (Cohon, 1978). From term 1 in (7) observe that if the minimum value m_k does not vary much from the maximum value M_k, the corresponding objective is not sensitive to a variation in the weighting values. Thus a small weight w_k can be assigned to this objective function. As the variation increases the weight becomes correspondingly larger. The second term in (7) normalizes the values taken by the objective function so that the effect of scale is mitigated. Hence, the α_k represent normalized weights for the various objectives which, in turn, depend upon the variation of the minimum value of the objective from the ideal solution. Lastly, the w_k are scaled to sum to unity in (6) to facilitate the comparison of different weighting strategies (Benayoun et al., 1971).

Continuing the calculation phase by solving (3)–(5) yields a solution $X^1 = (x_1^1, x_2^1, \ldots, x_n^1)$ and a vector of objective function values $(Z_k^*(X))$. These latter values are compared with the ideal solution to ascertain whether a satisfactory compromise has been achieved. If not, the decision making phase consists of asking the decision maker to indicate which objectives in the solution are attained at satisfactory levels allowing them to be reduced so that levels of unsatisfactory objectives may be improved. After identifying the satisfactory objectives (k^*) that can be reduced, and the permissible amount of reduction (ΔZ_k^*), the relative weights (w_k^*) of the satisfactory objectives are set equal to zero and all other weights are recomputed. A new feasible region F^{i+1} is defined such that it is equivalent to:

$$Z_k^*(X) \geqslant Z_k^*(X^i) - \Delta Z_k^*$$
$$\text{for all } k^* \text{ satisfactory objectives,} \tag{8}$$

$$Z_k(X) \geqslant Z_k(X^i)$$
$$\text{for all } p - k^* \text{ unsatisfactory objectives,} \tag{9}$$

$$X \in F^i. \tag{10}$$

The calculation phase is then re-entered with F^{i+1} and w_k (as modified) and a new solution to (3)–(5) is obtained. Cohon (1978) summarizes the major steps of this iterative process providing a ready reference for interested readers.

The iterations continue until the decision maker is satisfied with the results—an indication that a best compromise solution has been found. If, at any iteration the decision maker feels that none of the objectives are satisfactorily achieved, the algorithm stops with the conclusion that no best compromise solution can be found unless the decision maker is willing to make additional compromises. At most, p iterations are performed after which the decision maker is satisfied or it is concluded that no best compromise solution exists. The latter case implies that the decision maker is not willing to forfeit any amount of the satisfactory objectives to improve the unsatisfactory ones. Of course, it is always possible to ask the decision maker to reconsider previous decisions and relax one or more of the objectives. If this is not possible, then another solution procedure must be found.

The STEM method, with some modifications, has been applied in various fields. Dinkelbach and Isermann (1980) modified the STEM method by introducing lower and upperbounds on objective function values instead of using a pay-off table, and applied it to a problem of resource allocation in an academic department. A slight modification of this approach was also adopted by Loucks (1977) and Johnson and Loucks (1980) and applied to a water resources planning problem.

An illustrative example

Land use planning for publicly managed forests normally involves the allocation of certain areas of land to best achieve a balanced production of a

Table 1
Forest type and age class of case study area

Age class (years)	Douglas-fir (acres)	True fir (acres)
0– 10	27000	10500
11– 20	21600	7000
21– 30	19800	7000
31– 40	14400	6300
41– 50	14400	5600
51– 60	10800	4900
61– 70	10800	4200
71– 80	10800	2800
81– 90	10800	2100
91–100	10800	2100
100+	32400	17500
	183600	70000

variety of goods and services. Typically a consideration of timber, forage, wildlife, water, recreation and wilderness values are involved in this process. In order to demonstrate the role of MOP in the forest land use planning process, a simplified case study is presented. Only an integration of timber and wildlife are considered in this study, but the conceptual framework can incorporate other resource outputs and values.

The problem concerns a forest area consisting of Douglas-fir and true fir in the cascades of western Washington as characterized by the age class distribution shown in Table 1. Although the forest area is inhabited by numerous wildlife species, six have been selected as 'indicator' species representing the major life forms inhabiting the area. Table 2 shows the maximum number of animals (per year) that utilize the forest for either feeding and/or reproduction purposes during three successional stages of forest development.

For instance, on an acre [3] of young Douglas-fir (i.e., 31–80 years), approximately 3.2 Douglas squirrels either feed and/or reproduce. Likewise, about 2.8 Douglas squirrels feed and/or reproduce on an acre of mature true fir (i.e., 80+ years). Hence, the numbers in Table 2 represent the maximum number of animals that make use of an acre of forest land for feeding and/or reproduction activities. The data shown in Table 2 are hypothetical, but are believed to be reasonable estimates. Current information available in the wildlife literature is inadequate for providing a more conclusive quantitative base.

The objectives of management over the next 100 years are to: (a) maximize timber harvest plus ending inventory volume, (b) maximize the number of animals for five 'indicator' species (nos. 1–3 and 5–6) that utilize the area either for feeding and/or reproducing, and (c) minimize the

[3] One acre is equivalent to 0.404 hectares, and one thousand board feet (mbf) of standing volume is equivalent to approximately 5 cubic meters.

Table 2
Maximum number of animals that feed or reproduce (per acre per year) at various stages of forest development in case study area

Indicator species	Douglas-fir			True Fir		
	Seedling/sapling (0–30 yrs)	Young (31–80 yrs)	Mature (80+yrs)	Seedling/sapling (0–30 yrs)	Young (31–80 yrs)	Mature (80+yrs)
1. Pacific giant colomander			[X O] 100			[X O] 80
2. Douglas-squirrel	[X O] 1	[X O] 3.2	[X O] 4	[X O] 0.2	[X O] 1.6	[X O] 2.8
3. Black tailed deer	[X O] 0.12	[X O] 0.006	[X O] 0.018	[X O] 0.096	[X O] 0.0024	[X O] 0.012
4. Porcupine	[O] 0.021	[O] 0.021	[O] 0.018	[X O] 0.03	[O] 0.027	[X] 0.021
5. Hairy woodpecker		[X O] 0.30	[X O] 0.5		[X O] 0.20	[X O] 0.45
6. Gapper's red-backed vole	[X O] 4.5	[X O] 10.5	[X O] 15	[X O] 1.5	[X O] 7.5	[X O] 13.5

The symbol 'X' denotes that a species reproduces in the forest type.
The symbol 'O' denotes that a species feeds in the forest type.
The numbers under the X, O symbols reflect the maximum number of animals that use the area for feeding and/or reproduction activities per year.

tion of porcupines (species no. 4). Resource constraints which must be satisfied include: (a) acreage of forest land by type and age class and (b) nondeclining timber harvest flow policy imposed on a decadal basis. The major question facing the land manager is how to schedule timber harvesting activities over the 100-yr. planning horizon to best attain the stated objectives.

The approach adopted in this case study is to define a series of alternative timber harvesting schedules for each of the 10-yr. timber age classes defined in Table 1. Because a decadal nondeclining timber harvest flow constraint must be satisfied, the planning horizon is divided into 10-yr. planning periods. To keep the case study manageable, only two timber harvest alternatives are defined for each existing type and age class and other timber management activities such as thinning, fertilization and prescribed burning are not considered. Lastly, the spatial proximity of the age classes within the forest is not considered in the model.

The land manager's problem is to decide how many acres in each age class should be managed under each harvest alternative to best attain the stated objectives while satisfying the constraints. The large number of possible combinations of assignments of acres to harvest alternatives suggest the use of a MOP approach to the problem. And as previously discussed, the STEM method (a MOLP technique) is selected for this problem.

The initial phase of the STEM method involves the construction of a pay-off table. This is done by solving (1)–(2) for each of the p objective functions. For the case study, (1)–(2) take on the following form:

$$\begin{aligned} &\text{Max} \quad Z_k \quad \text{for } k = 1, 2, \dots, 7 \text{ and } k \neq 5, \\ &\text{Min} \quad Z_k \quad \text{for } k = 5 \end{aligned}$$

$$\left\{ = \sum_{j=1}^{11} \sum_{l=1}^{2} C_{kjl} X_{jl} + P_{kjl} Y_{jl}, \right. \tag{11}$$

subject to

$$\begin{aligned} &\sum_{l=1}^{2} X_{jl} \leqslant A_j \quad \text{for } j = 1, 2, \dots, 11, \\ &\sum_{l=1}^{2} Y_{jl} \leqslant B_j \quad \text{for } j = 1, 2, \dots, 11, \end{aligned} \tag{12)–(15}$$

$$\begin{aligned} &\sum_{j=1}^{11} \sum_{l=1}^{2} \left(V_{jlt} X_{jl} + V'_{jlt} Y_{jl} \right) \\ &\quad \geqslant \sum_{j=1}^{11} \sum_{l=1}^{2} \left(V_{jlt'} X_{jl} + V'_{jlt'} Y_{jl} \right) \\ &\quad \text{for } t = 2, 3, \dots, 10 \text{ and } t' = t - 1, \end{aligned}$$

where

C_{kjl}, P_{kjl} = k-th objective function coefficients denoting amount of timber or number of animals for 'indicator' species produced per acre of land in Douglas-fir or true fir, respectively, in age class j managed under alternative l,

X_{jl}, Y_{jl} = Number of acres of Douglas-fir or true fir, respectively, in age class j managed under alternative l,

A_j, B_j = Total number of acres of Douglas-fir or true fir, respectively, in age class j,

V_{jlt}, V'_{jlt} = Board foot harvest volume per acre in planning period t for Douglas-fir and true fir, respectively, in age class j managed under alternative l.

This problem involves seven objective functions which are: (a) maximize timber harvest plus ending inventory volume, (b) maximize the number of animals for 'indicator' species 1, 2, 3, 5 and 6, and (c) minimize the number of porcupines (i.e., 'indicator' species 4). In addition to the two sets of acreage constraints, a timber harvest flow constraint requires that the total timber harvest volume not decline from period to period and that the first period harvest be at least 1/2 billion board feet. [3]

Using data shown in Table 2, Tables 3a and 3b are constructed showing how different timber harvest alternatives affect the six "indicator" species and the volume of timber produced. Harvest alternatives are defined on the basis of rotation length and timing of the first harvest and all harvests occur at the end of a decade. Tables 3a and 3b define the various harvest alternatives by planning period for the two forest types. Columns 1 through 10 of each table are explicit descriptions of the harvest alternatives for each existing age class. Columns 11 through 16 contain the maximum number of "indicator" species that utilize the forest for a specified harvesting alternative.

For example, for the first age class in Table 3a

Table 3a
Definition of Douglas-fir timber harvest alternatives showing numbers of animals and timber volumes produced over 100-yr. planning horizon

Initial age class	Col.	1	2	3	4	5	6	7	8	9	10
		Planning period									
	Harvest alt.	1–10 1	11–20 2	21–30 3	31–40 4	41–50 5	51–60 6	61–70 7	71–80 8	81–90 9	91–100 10
0	1	–	–	–	–	H	–	–	–	–	H
	2	–	–	–	–	–	H	–	–	–	–
10	1	–	–	–	H	–	–	–	–	H	–
	2	–	–	–	–	H	–	–	–	–	H
20	1	–	–	H	–	–	–	–	H	–	–
	2	–	–	–	H	–	–	–	–	H	–
30	1	–	H	–	–	–	–	H	–	–	–
	2	–	–	H	–	–	–	–	H	–	–
40	1	H	–	–	–	–	H	–	–	–	–
	2	–	H	–	–	–	–	H	–	–	–
50	1	H	–	–	–	–	H	–	–	–	–
	2	–	–	–	H	–	–	–	–	H	–
60	1	H	–	–	–	–	H	–	–	–	–
	2	–	H	–	–	–	–	H	–	–	–
70	1	H	–	–	–	–	H	–	–	–	–
	2	–	–	–	–	H	–	–	–	–	H
80	1	H	–	–	–	–	–	H	–	–	–
	2	–	–	–	H	–	–	–	–	H	–
90	1	H	–	–	–	–	–	H	–	–	–
	2	–	H	–	–	–	–	–	H	–	–
100+	1	H	–	–	–	–	H	–	–	–	–
	2	–	–	–	–	H	–	–	–	–	H

11	12	13	14	15	16	17	18	19	20
Max. no. of species per acre						Harvest vol. (mbf)		Total harvest (mbf)	Ending inventory (mbf)
1	2	3	4	5	6	1st cut	2nd cut		
0	188	7.4	2.1	12	690	18	18	36	0
0	188	7.4	2.1	12	690	27	–	27	10
0	188	7.4	2.1	12	690	18	18	36	0
0	210	6.3	2.1	15	750	27	18	45	0
0	188	7.4	2.1	12	690	18	18	36	0
0	210	6.3	2.1	15	750	27	18	45	0
0	188	7.4	2.1	12	690	18	18	36	3.7
0	210	6.3	2.1	15	750	27	18	45	0
0	188	7.4	2.1	12	690	18	18	36	10
0	188	7.4	2.1	12	690	27	18	45	3.7
0	188	7.4	2.1	12	690	27	18	45	10
1000	240	5.3	2.1	20	855	51	18	69	0
0	188	7.4	2.1	12	690	35	18	53	10
0	188	7.4	2.1	12	690	43	18	61	3.7
0	188	7.4	2.1	12	690	43	18	61	10
4000	286	4.5	2.0	29	1050	63	18	81	0
1000	196	7.6	2.1	14	735	51	27	78	3.7
4000	264	5.6	2.0	26	990	63	18	81	0
1000	196	7.6	2.1	14	735	58	27	85	3.7
2000	226	6.5	2.0	19	840	63	27	90	0
1000	196	7.6	2.1	14	735	63	18	81	10
5000	294	4.6	2.0	31	1095	63	18	81	0

H = harvest activity.
– = no harvest activity.
mbf = one thousand board feet (see footnote 3).

Table 3b
Definition of true fir timber harvest alternatives showing numbers of animals and timber volumes produced over 100-yr. planning horizon

Initial age class	Col.	1	2	3	4	5	6	7	8	9	10
		Planning period									
	Harvest alt.	1–10 1	11–20 2	21–30 3	31–40 4	41–50 5	51–60 6	61–70 7	71–80 8	81–90 9	91–100 10
0	1	–	–	–	–	–	H	–	–	–	–
	2	–	–	–	–	–	–	H	–	–	–
10	1	–	–	–	–	H	–	–	–	–	–
	2	–	–	–	–	–	H	–	–	–	–
20	1	–	–	–	H	–	–	–	–	–	H
	2	–	–	–	–	H	–	–	–	–	–
30	1	–	–	H	–	–	–	–	–	H	–
	2	–	–	–	H	–	–	–	–	–	H
40	1	–	H	–	–	–	–	–	H	–	–
	2	–	–	H	–	–	–	–	–	H	–
50	1	H	–	–	–	–	–	H	–	–	–
	2	–	H	–	–	–	–	–	H	–	–
60	1	–	–	H	–	–	–	–	–	H	–
	2	–	H	–	–	–	–	–	H	–	–
70	1	H	–	–	–	–	–	H	–	–	–
	2	–	H	–	–	–	–	–	H	–	–
80	1	H	–	–	–	–	–	H	–	–	–
	2	–	–	–	H	–	–	–	–	–	H
90	1	H	–	–	–	–	–	H	–	–	–
	2	–	–	H	–	–	–	–	–	H	–
100+	1	H	–	–	–	–	H	–	–	–	–
	2	–	H	–	–	–	–	H	–	–	–

11	12	13	14	15	16	17	18	19	20
Max. no. of species per acre						Harvest. vol. (mbf)		Total harvest (mbf)	Ending inventory (mbf)
1	2	3	4	5	6	1st cut	2nd cut		
0	76	5.9	2.9	8	390	17	–	17	3
0	76	5.9	2.9	8	390	24	–	24	0
0	90	4.9	1.4	10	450	17	–	17	10
0	90	4.9	1.4	10	450	24	–	24	3
0	104	4.0	2.8	12	510	17	17	34	0
0	104	4.0	2.8	12	510	24	–	24	10
0	104	4.0	2.8	12	510	17	17	34	0
0	118	3.0	2.8	14	510	24	17	41	0
0	90	4.9	1.4	10	450	17	17	34	0
0	104	4.0	2.8	12	510	24	17	41	0
0	76	5.9	2.9	8	390	17	17	34	0
0	90	4.9	1.4	10	450	24	17	41	0
800	116	4.1	2.8	14.5	570	34	17	51	0
0	90	4.9	1.4	10	450	30	17	47	0
0	76	5.9	2.9	8	390	30	17	47	0
800	102	5.0	2.8	12.5	510	34	17	51	0
800	88	6.0	2.8	10.5	450	34	17	51	0
3200	166	3.4	2.6	24	810	47	17	64	0
800	88	6.0	2.8	10.5	450	39	17	56	0
2400	140	4.3	2.6	19.5	690	47	17	64	0
800	88	6.0	2.8	10.5	450	43	10	53	3
1600	100	6.0	2.8	13	510	47	10	57	0

H = harvest activity.
– = no harvest activity.
mbf = one thousand board feet (see footnote 3).

under harvest alternative 1, it is shown that a maximum of 188 Douglas squirrels (indicator species no. 2) make use of an acre of the Douglas-fir type (either by feeding and/or reproducing) over the 100-yr. planning horizon. This coefficient is derived by observing that under harvest alternative 1 for age class 0 in Table 3a, harvests are scheduled for periods 5 and 10. For periods 1 through 4, no harvests are made, allowing the forest to develop and grow. During this period of stand development, 1 Douglas squirrel per year will feed and/or reproduce during the seedling stage (0-30 years) and 3.2 squirrels per year will feed and/or reproduce during the young stage (31-80 years). Hence, from periods 1 through 5 a maximum of 94 (i.e., $(30 * 1) + (20 * 3.2)$) Douglas squirrels will feed and/or reproduce on an acre of Douglas-fir which is presently zero yrs. old. Referring to Table 3a, harvest alternative 1 further specifies no cutting during periods 6 through 9. Hence, during the second rotation (i.e., periods 6 through 10), it is estimated that another 94 Douglas squirrels will make use of an acre during the seedling (0-30 years) to young (31-80 years) stages of stand development. Therefore, a maximum of 188 Douglas squirrels will make use of an acre of the stand during the entire planning period. This number is entered under column 12 for the first age class under harvest alternative 1 and becomes equivalent to objective function coefficient $C_{2,1,1}$. Similar calculations lead to the other production coefficients shown in Tables 3a and 3b.

The timber harvest volumes shown in columns 17-20 were obtained from existing yield tables, and are expressed in thousands of board feet. [3] For example, in the formal model, coefficient $V_{2,1,4} = 18$ mbf and represents the per acre board foot volume expected in the Douglas-fir type; initial age class 2; harvest alternative 1; and planning period 4. Similarly, objective function coefficient $C_{1,2,1} = 36$ mbf.

Summary of compromise solutions

The first step of the STEM method consists of sequentially solving (11)–(14) for each objective function. Results of these runs are shown in the pay-off table (Table 4). As shown, the simultaneous optimization of all seven objectives is not possible. Thus, a compromise solution must be found.

Table 5 describes a summary of three compromise solutions obtained using the STEM method. The weights used to reflect the decision maker's preferences for the various objectives are calculated using a modified form of (6)–(7). The modification involves the substitution of previously scaled objective function coefficients. Using the pay-off table (Table 4) and (6)–(7), as modified, an initial set of weights are calculated as shown in Table 6. These initial weights are included in (4) and are used to derive the first compromise solution as shown in Table 5. In calculating the first compromise solution, greater weight is assigned to species 1, 2, 4, and 5 as these exhibit the largest relative variation from their respective objective function values. Further, since objective 5 is to be minimized, (4) is rewritten as $D \geqslant w_5\ [Z_5(X) - M_5]$.

From Table 5 the decision maker judges that the first compromise solution provides output levels for 'indicator' species 2, 3, 5, and 6 in excess of what is deemed satisfactory. Thus, the decision maker is willing to settle for a reduced level of output to allow for the reallocation of resources to better attain remaining objectives. Specifically, the decision maker is willing to settle for an output level for these species which is 15% below their maximum values. These reduced values form the right hand sides of (8), for $k^* = 3$, 4, 6, and 7, respectively, and the right hand sides of (9) are set equal to the output levels for the first compromise solution for the remaining $p - k^*$ unsatisfactory objectives.

Eqs. (8)–(9) are appended to (3)–(5), thus redefining F^{i+1} and a second compromise solution is obtained. In arriving at this solution a new set of weights are used. Specifically, w_3, w_4, w_6, and $w_7 = 0$, as these objectives are satisfactorily achieved, and the weights for the remaining unsatisfactory objectives are calculated using (6)–(7).

The second compromise solution shown in Table 5 results in improved output levels for the unsatisfactory objectives (i.e., timber harvest, species 1, and species 4). Further, although a 15% reduction for the satisfactory objectives was permitted, the second compromise solution shows that the attainment levels for species 2, 5, and 6 are actually less than 15% from their maximum

Table 4
Pay-off table for case study

Solution	Timber harv. mbf	Numbers of animals ('000)					
		Species 1	Species 2	Species 3	Species 4	Species 5	Species 6
1	6302891	22498	25365	1035	343	1911	100203
2	5165468	46611	19581	781	271	1548	77699
3	5271883	20924	25681	1029	336	1898	99740
4	6152468	14319	25296	1043	346	1875	99215
5	5180020	21487	19596	764	258	1524	76942
6	6294695	28412	25451	1029	343	1921	99911
7	6302684	25139	25644	1036	343	1916	100322

mbf = one thousand board feet (see footnote 3).
The underlined numbers represent the ideal solution.

values. Only species 3 was reduced the full 15% in the second compromise solution.

After being presented with the second compromise solution, the decision maker decides that only species 1 is not being produced at a satisfactory level. To free-up additional resources, it is decided that output levels for species 2, 3, 5, and 6 can be reduced up to 15% from their respective maximum values. Likewise, species 4 may be increased up to 15% above its minimum value. However, no reduction in the current attainment of timber harvest volume is permitted. Thus, only a maximum difference of 12.8% is to be tolerated. Because only species 1 is judged to be unsatisfactorily achieved, no recalculation of weights is necessary.

The results of the third compromise solution are shown in Table 5. By allowing species 4 to deviate more from its minimum level, more timber harvest volume and greater numbers of species 1, 2, 5, and 6 are produced. Only species 3 output remains unchanged from compromise solution two. At this point, the decision maker considers all of the objectives to be satisfactorily achieved and the STEM algorithm is terminated.

Table 5
Summary of three compromise solutions for case study

Objective function ('000)	Maximum/ minimum	First compromise	% Diff. from maximum/ minimum	Second compromise	% Diff. from maximum/ minimum
Timber harv. species	6302891	5143956	18.4	5494317 *	12.8
1	46611	35238	24.4	37530	19.5
2	25681	23064 *	10.2	22297 *	13.2
3	1043	918 *	12.0	887 *	15.0
4	258	297	15.1	289 *	12.0
5	1921	1709 *	11.0	1661 *	13.5
6	100322	89353 *	10.9	86528 *	13.7

Objective function ('000)	Third compromise	% Diff. from maximum/minimum
Timber harv. species	5573766 *	11.6
1	39857 *	14.5
2	22341 *	13.0
3	887 *	15.0
4	292 *	13.2
5	1682 *	12.4
6	87018 *	13.3

* Objectives judged to meet or exceed satisfactory levels.

Table 6

Objective function	α_k (eq. (7))	w_k (eq. (6))
1. Timber harv.	0.00050	0.0321
2. Species 1	0.00741	0.4759
3. Species 2	0.00214	0.1374
4. Species 3	0.0067	0.0430
5. Species 4	0.00220	0.1413
6. Species 5	0.00212	0.1362
7. Species 6	0.00053	0.0340
	0.01557	1.000

Summary and discussion

In this paper, the STEM method (an interactive MOLP technique) is illustrated as an appropriate forest land management planning procedure. Because of its computational efficiency and simple algorithmic procedure, it appears to be a useful tool for forest planners to consider. Its main disadvantage is its inability to generate explicit trade-off information.

Bare and Kitto (1979) believe that no MOP method will solve all land management planning problems. Further, to be effective, an analytical methodology should be used to identify and formulate new alternatives and not to determine the optical solution to the planning problem. Forest planners should recognize that the principal use of MOP techniques is to provide a systematic and analytical approach to help identify and facilitate an evaluation of new alternatives and not to produce an 'instant plan'.

Forest land management planning systems are 'wicked systems' whose elements can not be sufficiently captured by any single MOP technique (Brill, 1979; Liebman, 1976). Brill (1979) advocates the joint use of simulation and optimization models to address these problems. This approach may be useful in forest land use planning and should be evaluated.

Another important concern in forest land management planning involves the integration and coordination of multiple decision makers. Ecology, environmental planning, politics and forest management are just a few of the disciplines involved in forest land management planning. Analysis of multiple decision maker problems is just beginning to attract the interest of forest management scientists and resource planners. However, with the emphasis placed on public input it is clear that this area deserves increased attention.

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