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The Development of Multiple Objective Programming Methods for Forest Land Management Planning: A Survey and Evaluation

by

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Abstract

Multiple objective programming (MOP) has undergone a rapid period of development in the 1970's. Concurrently, increased land-use pressures have stimulated forest land management analysts to develop and utilize more sophisticated planning aids to address complex multiple use issues involving multiple objectives and decision-makers. In this paper, a selected set of MOP methodologies are reviewed and evaluated in terms of their utility and applicability as land management planning tools. The STEP method is selected as an appropriate technique and is applied to a forest land management problem. Two objective function weighting procedures are illustrated. Although no MOP technique by itself can resolve land management conflicts, the STEP method offers promise as a rational-systematic means of exploring alternative feasible solutions to the multiple objective forest land management problem.

Multiple Objective Programming (MOP) or Multi-Criteria Decision Making (MCDM) 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. The applicability of MOP as a planning tool for forest land management planning is the primary motivation of this paper.

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The application of mathematical programming to forest land management has been limited mainly to linear programming (LP) and goal programming (GP). Despite the fact that multiple use has been recognized, and regarded by some as an operational concept, for almost two decades [25], 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 [1], [4], [5], [6], [13], [14], [15], [19], [20], [21], [29], [30], [31], [32]. Recently, however, questions concerning the inappropriateness of GP to capture the vital characteristics and elements of forest land management planning have been raised. The most intriguing implications of GP are those described by Cohon and Marks [12] and Dyer et al. [16]. These implications will be discussed in detail in a latter section.

The potential of MOP methods as analytical aids for future land management planning systems appears very promising [3]. For example, recent amendments to the National Forest Management Act of 1976 (NFMA) require the use of a new systematic and analytical planning approach to land use planning for the National Forests. The growing awareness among forest management scientists of the use of MOP techniques is evidenced by several recent papers describing forestry applications [2], [9], [15], [34].

The development of MOP techniques has been largely due to professionals responsible for optimizing the management of water resources. However, during recent years, management scientists have also made significant contributions. A comprehensive review of MOP methods is discussed in Cohon [11]. In this paper, only a selected number of MOP methodologies will be reviewed in order to highlight their characteristic features and evaluate their applicability to forest land management planning. Readers interested in a detailed discussion of these and other methods are encouraged to refer to [2], [11]. A case study is also presented to demonstrate the use of one MOP methodology.

Mathematical Background

The general MOP problem involving p objectives (Z_k), n decision variables (X_j) and m constraints (g_i) with b_i right hand sides may be expressed as:

$$\text{Max } Z(X_1, X_2, \ldots, X_n) = [Z_k(X_1, X_2, \ldots, X_n) \text{ for } k = 1,2, \ldots p] \quad (2.1)$$

subject to:

$$g_i(X_1, X_2, \ldots, X_n) \leq b_i \text{ for } i = 1, 2, \ldots m \quad (2.2)$$

$$X_j \geq 0 \text{ for } j = 1, 2, \ldots, n$$

where Z is a vector valued function consisting of the objective functions $Z_k(X_j)$, for $k = 1,2, \ldots p$.

If Z_k (X_j) and g_i for all i = 1,2, . . . , m and k = 1,2, . . . ,p are linear with respect to X_j for all j = 1,2, . . . ,n, the multiobjective problem is referred to as a multiple objective linear program (MOLP). In this case the problem described in (2.1) and (2.2) can be expressed as:

$$
\begin{aligned}
\text{Max } Z_1 &= C_{11} X_1 + C_{12} X_2 + \ldots + C_{1n} X_n \\
\text{Max } Z_2 &= C_{21} X_1 + C_{22} X_2 + \ldots + C_{2n} X_n \\
\text{Max } Z_p &= C_{p1} X_1 + C_{p2} X_2 + \ldots + C_{pn} X_n
\end{aligned}
\qquad (2.3)
$$

subject to:

$$
\begin{aligned}
a_{11}X_1 + a_{12}X_2 + \ldots + a_{1n} X_n &\leq b_1 \\
a_{21}X_1 + a_{22}X_2 + \ldots + a_{2n} X_n &\leq b_2 \\
\vdots \qquad \vdots \qquad\qquad & \quad \vdots \\
a_{m1}X_1 + a_{m2}X_2 + \ldots \; a_{mn} X_n &\leq b_m
\end{aligned}
\qquad (2.4)
$$

where

C_{kj} = objective function coefficients associated with objective function k and decision variable X_j.

Z_k = objective function value for objective k

a_{ij} = technological coefficients associated with constraint i and decision variable X_j.

b_i = limiting value of ith input resource.

The formulation in (2.3) and (2.4) closely parallels, and is an extension of, classical LP. However, 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 (2.1) cannot be optimized except for the trivial case where an "ideal solution" exists (i.e. all objectives are complementary and can be maximized simultaneously). Hence, in MOP, a different conceptual view of optimization is required.

To approach this formally, all feasible solutions to (2.3) and (2.4) are classified into two mutually exclusive sets: (a) nondominated [sometimes called non-inferior or pareto-optimal] solutions or (b) dominated [or inferior] solutions[1].

Clearly, a decision maker would like to select a nondominated solution as the preferred choice. However, in the presence of multiple competing objectives there will be several (perhaps 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 is 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 weighing each objective. The preferred nondominated solution is labelled the "best compromise" reflecting the fact that "best" is dependent upon the articulated preferences.

Multiobjective Programming Methods

MOP techniques can be classified into three categories: (a) generating techniques, (b) noniterative techniques where the preferences are articulated prior to the analysis, and (c) iterative techniques which incorporate preferences through an interactive process involving the analyst and the decision maker.

Generating Techniques

Generating techniques refer to those approaches whereby the analyst generates the entire set of nondominated solutions in the absence of any preference information from the decision maker. Given this set of solutions, the decision maker applies his preference structure to arrive at the best compromise.

Several approaches have been suggested for generating the entire nondominated set. Among these are the multi-criteria simplex [18], [37]; methods based on weights [22], [26], [28], [36]; and constraint methods [24]. Only a discussion of the latter method will be presented to convey the general nature of these approaches.

The constraint method is intuitively appealing because one objective is selected for optimizing while all remaining objectives are constrained to some pre-specified value [24]. The method works by generating a pay-off table which contains the values of p objective functions. The optimal value for each of the p objective functions is recorded on the diagonal of the pay-off table and the off-diagonal elements are computed by evaluating each objective function at each of the optimal solutions. The largest and smallest number in each column represents the range over which the right hand side of each constraint is parametrically varied while one of the selected objectives is optimized. To facilitate the parametric programming, only a selected number of different values within the range are examined.

This method suffers from the excessive computational burden required to conduct the parametric analysis of each right hand side. For example, given p objective functions and r values for each right hand side there are r^{p-1} linear programming problems to solve. While parametric linear programming can reduce this computational burden, it still is excessive for realistic-sized land management planning problems.

Noniterative Techniques

Noniterative techniques require that the decision maker articulate preferences prior to the analysis. These methods avoid generating the entire set of nondominated solutions but they require considerable information concerning goal preferences before any knowledge of trade-offs is known [11]. Techniques representative of this approach include: (a) utility theory, (b) goal programming and (c) the surrogate worth trade-off.

Goal programming has been extensively discussed in the forest land management literature [4], [15], [16], [19], [21]. Thus, attention here will focus on only a few of the relevant characteristics of goal programming.

Perhaps the most widely discussed feature of goal programming is its ability to incorporate cardinal weights as well as ordinal rankings to facilitate the expression of goal preferences. Several authors have discussed the disadvantages associated with ordinal rankings expressed through preemptive priority factors [11], [16], [21]. Particular problems encountered when using preemptive priorities include: (a) the possible selection of a dominated solution as the preferred alternative and (b) the acceptance of an infinite trade-off ratio between goals ranked at different priority levels. These problems can be alleviated by using either cardinal weights or only minimizing negative deviations of ordinally ranked goals.

The surrogate worth trade-off method involves the computation of trade-offs between successive pairs of objective functions. This is done to approximate the decision maker's utility function for a subset of nondominated solutions. This subset is generated by transforming a p-objective problem into a two-objective problem where one objective, r, is maximized while a second objective, q, is constrained to be greater than or equal to some specified level, L_q. The remaining p-2 objectives are set equal to some level, L_k. By parametric variation of L_q, a portion of the nondominated set is approximated.

In addition to tracing out a portion of the nondominated set, the above process also provides trade-off information between objectives r and q. This trade-off, t_{rq}, varies with the different levels assigned to L_q. These trade-offs are presented to the decision maker to elicit information about the implicit utility function being approximated. The decision maker provides a value, w_{rq}, (labeled the surrogate worth) for each t_{rq}.

The method is based on the premise that given a nondominated solution, a decision maker will compare the magnitude of t_{rq} (the slope of the nondominated set) with the marginal rate of substitution (MRS) between the value of objectives r and q (the slope of the indifference curve) [11]. If t_{rq} is less than the MRS for a given value of objective r then a positive surrogate worth is assigned to w_{rq}. Surrogate worths are restricted to lie in the interval $\pm$ 10, depending upon the decision maker's valuation of trade-offs. When the slope of the nondominated set equals the slope of the indifference curve, a surrogate worth of zero is assigned. The set of w_{rq} for all assigned values of

L_q represents the surrogate worth function.

The best compromise solution for objectives r and q is identified at the point where the slope of the nondominated set and the slope of the indifference curve are equal. Following this, the remaining objectives are considered in pair-wise fashion. This analysis results in the generation of p-1 surrogate worth functions. The value (Z_q) for p-1 of the objectives is calculated at the point where the surrogate worth function equals zero. Then, the remaining-arbitrarily selected objective is maximized subject to the constraint that the remaining objectives be greater than or equal to Z_q.

Interactive Techniques

Interactive techniques are those which provide for interaction between the decision maker and the analyst and lead to an articulation of preferences by the decision maker as nondominated solutions are presented at each iteration. With new preference information provided at each iteration, the analyst generates another nondominated solution for the decision maker to examine. Through this interactive process, the decision maker eventually arrives at the best compromise solution.

Several techniques which follow the interactive approach are: (a) the STEP method developed by Benayoun et al. [7], (b) the method of Zionts and Wallenius [38], and (c) Steuer's method [33]. Because of its conceptual appeal and computational efficiency, the STEP method is a promising tool for forest land management planning. Thus, it is discussed in detail in the following paragraphs. Steuer's method is discussed and applied to a forestry problem in Steuer and Schuler [34]. Other interactive techniques are those of Dyer [17], Benson [8] and Geoffrion, Dyer and Feinberg [23]. An evaluation of some of these methods is given by Wallenius [35].

The STEP method of Benayoun et al. [7] is based on the concept of the ideal solution. However, while the ideal solution approach is essentially a non-iterative method, the STEP method relies on an interative approach for identifying the best compromise solution. The ideal solution is defined as that solution which simultaneously optimizes each objective when considered individually. Generally this solution is infeasible. If it isn't, there is no conflict as all objectives can be met simultaneously.

If the ideal solution is infeasible, the feasible solution which is "closest" to the ideal is identified. Different solutions can be found depending upon the decision maker's definition of "closest." In general, the distance between two points X and Z with coordinates $(X_1, X_2, \ldots, X_p)$ and $(Z_1, Z_2, \ldots, Z_p)$ is:

$$d_\alpha = \{\Sigma|X - Z|^\alpha\}^{1/\alpha}$$

$$\text{where } 1 \leq \alpha \leq \infty \tag{2.5}$$

Thus depending upon the value selected for α —the distance metric — a different solution can be obtained.

If $\alpha = 1$, and we ignore the absolute value sign in (2.5), the best compromise solution is equivalent to an equal weighting of each objective. Thus, minimizing the deviation between the ideal solution and the best compromise solution is equivalent to equally weighting each objective [11]. At the extreme, if $\alpha = \infty$ the largest deviation between the ideal and the best compromise solution determines the final compromise.

In general, as the distance metric is varied, a series of compromise solutions, forming a subset of the set of nondominated solutions, is generated. Zeleny [37] refers to this as the "compromise set." It is left to the decision maker to select the distance metric to employ in any particular decision situation.

The STEP method, seeks to identify the best compromise solution by presenting sequential compromise solutions with each reflecting the decision maker's preferences. Each iteration consists of a calculation phase and a decision making phase. The method begins with the construction of a pay-off table which is found by solving (2.3 – 2.4) 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 where the maximum value of each objective is realized.

The calculation phase of the STEP algorithm seeks to find a compromise feasible solution which is "nearest" to the ideal solution. This is accomplished by minimizing the maximum difference D between the p objective function values and their respective maximum values M_k. This involves solving the LP problem:

$$\text{Minimize } D \tag{2.6}$$

subject to

$$D \leq w_k \left[M_k - Z_k(X_1, X_2, \ldots, X_n) \right] \text{ for } k = 1, 2, \ldots, p \tag{2.7}$$

$$x \in X^1 \tag{2.8}$$

Constraint (2.7) ensures that D is no larger than each weighted (w_k) difference between the maximum value and the actual value of each objective. Eq. (2.8) defines the feasible region as constrained by the m resource constraints identified in (2.4). The feasible region is reduced at each iteration. That is, $x^1 = x$ for i = 1 but x^i for $i > 1$ is a modified form of x which incorporates the decision maker's reaction to the solution found at the (i-1)th iteration.

The weights (w_k) 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 decision maker may be used, or (c) the following formula approach may be adopted. In the latter approach, the weights include two components; a scaling term

(2.9) and a normalizing term (2.10). They are calculated as:

$$w_k = \alpha_k / \Sigma\alpha_k \tag{2.9}$$

$$\text{where } \alpha_k = \underbrace{\frac{M_k - m_k}{M_k}}_{\text{Term 1}} \cdot \underbrace{\left[\Sigma c_{kj}^{\;2}\right]^{-1/2}}_{\text{Term 2}} \tag{2.10}$$

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 for the k^{th} objective function.

From term 1 in (2.10), observe that if the value of Z_k does not vary much from the maximum value, 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 (2.10) normalizes the values taken by the objective function. Thus, w_k represent normalized weights on the various objectives which in turn depend on the variation of the value of the objective from the ideal solution. Lastly, the w_k are scaled to sum to unity (2.9).

Solving (2.6-2.8) yields a solution $x^o = (x_1^o, x_2^o, \ldots, x_n^o)$ and a vector of objective function values. These latter values are compared with the ideal solution to ascertain whether a satisfactory compromise has been achieved. If not, the next step (decision making phase) consists of asking the decision maker to indicate which objectives in the solution are attained at satisfactory levels and which can be reduced so that levels of unsatisfactory objectives may be increased. The decision maker must identify the satisfactory objectives Z_k^* (X^o) that can be reduced and the permissible amount of reduction ΔZ_k^*. Before the next iteration, the relative weights (w_k) of the satisfactory objectives are set equal to zero. The feasible region X^1 is modified by the additional constraints;

$$Z_k^*(x) \geq Z_k^* \; (X^0) - \Delta\, Z_k^* \text{ for all } k^* \tag{2.11}$$

$$Z_k(x) \geq Z_k \; (X^0) \text{ for all } k \neq k^* \tag{2.12}$$

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 exists. 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.

Evaluation of Techniques

Cohon and Marks [12] established three criteria for judging the applicability of the various MOP techniques: (a) computational feasibility, (b) explicit quantification of trade-offs among objectives and (c) production of sufficient information to facilitate an informed decision. Bare, Mendoza and Mitchell [2] established two classes of evaluative criteria: (a) applicability and (b) utility. In order that a method be regarded as applicable to a forest land management planning problem, it must possess the following characteristics: (a) assumptions must not be violated by the land use planning situation, (b) data requirements must be feasible, and (c) it must be able to computationally solve the formulated problem at a reasonable expense. On the other hand, the utility of a MOP technique can be judged by: (a) the explicitness of trade-offs, (b) the complexity of the methodology, and (c) the degree of prior application to related problems. These evaluative criteria will be used to judge the appropriateness of the MOP techniques discussed above.

Generating techniques are regarded as inappropriate for the forest land management problem because they generally fail to meet the computational requirements associated with land use problems. Furthermore, no trade – off information is provided to the decision maker. Although the methods are quite complex, data requirements do not appear to be a limiting consideration. Cohon [11] prefers the generating methods because they clearly identify the role of the analyst as an "information provider", not actively engaged in the decision making process. Nevertheless, we believe the methods involve excessive computations to make them valuable as land management planning tools.

Some of the noninteractive methods appear to be useful for forest land use planning. In particular, GP, which has been applied to forest land management problems, appears to hold great promise. The computational requirements are acceptable and the method is easy to understand. Trade-offs between objectives are available if cardinal weights are employed and, with the exception of providing these weights, the data requirements are not excessive. The generation of dominated solutions through the use of preemptive priorities is a drawback of GP. However, ways to circumvent this are available.

Although the surrogate worth trade-off is a powerful technique, its excessive computational burdens rule it out as a possible technique for realistic-sized forest land use planning problems. Further, the complexity of the technique is also a disadvantage. Finally, it requires information from the decision maker that is not usually available.

The authors believe that the interactive methods offer the best promise for multi-objective forest land management planning problems. The general approach of these techniques facilitates the development of preference information during the problem solving session to permit an efficient search for the best compromise solution. The ideal solution and the STEP method are the two most appropriate techniques based on the evaluative criteria outlined previously. These methods are applicable to forest land management planning problems in that they can computationally accommodate problems of the size encountered and the methodologies are easy to understand. The only disadvantage is that trade-offs are not explicitly generated.

The most important difference between the ideal solution and the STEP method is that the latter permits the decision maker to change the feasible region at each iteration. We believe this is important because it encourages the decision maker to concentrate on attainment of objectives and not on the distance metric. The STEP method also uses the highly efficient simplex which is familiar to forest planners. The method works towards a best compromise solution by trying to minimize the distance between the ideal solution and the best compromise. This is intuitively appealing as it clearly shows that compromises must be made between different functions if the best compromise solution is to be identified. The method is not as complex nor as computationally demanding as the surrogate worth trade-off method. However, an explicit calculation of trade-offs between objective functions is not provided as part of STEP.

An Application of the STEP Method

Land use planning for publicly managed forests normally involves the allocation of certain areas of land to best achieve a balanced production of a 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 the example, but the conceptual framework is flexible to incorporate other resource outputs and values.

The problem concerns a forest area of 253,000 acres with 183,000 acres predominantly covered by Douglas-fir and 70,000 acres covered by true fir in the cascades of western Washington. The age class distribution in terms of the area occupied by each age class is shown in Table 1.

The forest area is inhabited by numerous wildlife species. However, six species are selected as "indicator" species representing six major life forms believed to be the major inhabitants in the area. Table 2 shows the approximate number of species that feed and/or reproduce during three successional stages of forest development. The data shown in Table 2 are hypothetical, but are reasonable estimates. Information available in the wildlife literature is inadequate for providing a more conclusive quantitative base.

From Table 2, Tables 3a and 3b are constructed showing how different management alternatives affect the six indicator species. Management alternatives are defined on the basis of rotation and timing of the first harvest. A 100-yr. planning horizon is specified and divided into 10-yr. planning periods. Two management alternatives are specified for each age class.

Table 1. Cover Type and Age Class of Case Study Area

Age class (Acres)	Douglas-fir Area (Acres)	True fir Area
0-10	27,000	10,500
11-20	21,000	7,000
21-30	19,800	7,000
31-40	14,400	6,300
41-50	14,400	5,600
51-60	10,800	4,900
61-70	10,800	4,200
71-80	10,800	2,800
81-90	10,800	2,100
91-100	10,800	2,100
100+	32,400	17,500
	183,000	70,000

Table 2. Approximate number of species that feed or reproduce at various stages of forest development in case study area.

	Indicator Species	Douglas-fir Forb-brush/ Seedling (0-25)	(Ave. site = 110) Young (25-80 yrs)	Mature (80+years)	True fir Forb-brush/ Seedlings (0-25)	(Ave. Site = 80) Young (25-80 yrs)	Mature (80+yrs)
1.	Pacific Giant Colomander			[X 0] 100			[X 0] 80
2.	Douglas squirrel	[X 0] 1	[X 0] 3.2	[X 0] 4	[X 0] .2	[X 0] 1.6	[X 0] 2.8
3.	Black tailed deer	[X 0] .12	[X 0] .006	[X 0] .018	[X 0] .096	[X 0] .0024	[X 0] .012
4.	Porcupine	[0] .021	[0] .021	[0] .018	[X 0] .03	[0] .027	[X] .021
5.	Hairy woodpecker		[X 0] .30	[X 0] .5		[X 0] .20	[X 0] .45
6.	Gapper's red-backed vole	[X 0] 4.5	[X 0] 10.5	[X 0] 15	[X 0] 1.5	[X 0] 7.5	[X 0] 13.5

x = reproduction
0= feeding

TABLE 3a. Definition of Douglas Fir Management Alternatives by Planning Period.

Mgmt Unit Age Class	Mgmt 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	No. of Species Per Acre 1	2	3	4	5	6	Harvest Vol (bd. ft.) 1st cut	2nd cut	Ending Inventory Vol. (bd. ft.)	Total Vol. (bd. ft.)	Variable
1-10	1	N	N	N	N	H	N	N	N	N	N	0	8.4	.152	.084	.3	30	30577	30577	0	61154	X1,1
	2	N	N	N	N	N	H	N	N	N	N	0	8.4	.152	.084	.3	30	40277	0	30577	70854	X1,2
11-20	1	N	N	N	H	N	N	N	N	H	N	0	8.4	.272	.105	.3	25.5	30577	30577	4127	65291	X2,1
	2	N	N	N	N	H	N	N	N	N	H	0	8.4	.152	.084	.3	30	40277	30577	0	70854	X2,2
21-30	1	N	N	H	N	N	N	N	H	N	N	0	8.4	.152	.084	.3	34.5	30577	30577	11748	72902	X3,1
	2	N	N	N	H	N	N	N	N	H	N	0	8.4	.152	.084	.3	30	40277	30577	4137	74991	X3,2
31-40	1	N	H	N	N	N	N	H	N	N	N	0	8.4	.152	.084	.3	30	30577	30577	20880	82034	X4,1
	2	N	N	H	N	N	N	N	H	N	N	0	8.4	.152	.084	.3	30	40277	30577	11748	82602	X4,2
41-50	1	N	N	H	N	N	N	N	H	N	N	0	8.4	.152	.084	.3	30	49639	30577	11748	91964	X5,1
	2	N	H	N	N	N	N	H	N	N	N	0	8.4	.152	.084	.3	30	40277	30577	20880	91734	X5,2
51-60	1	H	N	N	N	N	H	N	N	N	N	0	11.6	.158	.063	.3	30	40277	30577	30577	101431	X6,1
	2	N	N	N	H	N	N	N	N	H	N	100	8.2	.264	.081	.8	34.5	58450	30577	4137	93164	X6,2
61-70	1	H	N	N	N	N	H	N	N	N	N	100	5.2	.158	.063	.6	30	49639	30577	30577	110793	X7,1
	2	N	H	N	N	N	N	H	N	N	N	0	8.4	.152	.084	.3	34.5	58450	30577	20880	109907	X7,2
71-80	1	H	N	N	N	N	H	N	N	N	N	100	5.2	.158	.063	.6	30	58450	30577	30577	119604	X8,1
	2	N	N	N	N	H	N	N	N	N	H	0	8.2	.144	.081	1.1	30	73970	30577	0	104497	X8,2
81-90	1	H	N	N	N	N	N	H	N	N	N	0	5.2	.170	.063	.6	30	73970	30577	20880	125427	X9,1
	2	N	N	N	H	N	N	N	N	N	N	100	8.2	.144	.081	1.1	30	73970	30577	49639	154186	X9,2
91-100	1	H	N	N	N	N	N	H	N	N	N	100	8.2	.144	.081	1.1	30	66586	30577	20880	108410	X10,1
	2	N	H	N	N	N	N	N	H	N	N	100	8.2	.144	.081	1.1	30	73970	30577	11748	106662	X10,2
100+yrs.	1	H	N	N	N	N	N	N	N	N	N	100	8.2	.144	.081	1.1	30	66586	30577	66586	154116	X11,1
	2	N	N	N	H	N	N	N	N	N	H	100	8.2	.144	.081	1.1	30	73970	30577	0	94914	X11,2

H = Harvest

N = No harvest

TABLE 3b. Definition of True Fir Management Alternatives by Planning Period.

Mgmt Unit Age Class	Mgmt 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	No. of Species Per Acre 1	2	3	4	5	6	Harvest Vol (bd. ft.) 1st cut	2nd cut	Ending Inventory Vol. (bd. ft.)	Total Vol. (bd. ft.)	Variable
1-10	1	N	N	N	N	N	H	N	N	N	N	0	3.6	.1968	.114	.4	18	20944	0	15556	36500	Y1,1
	2	N	N	N	N	N	N	H	N	N	N	0	3.6	.1968	.114	.4	18	26077	0	101953	36272	Y1,2
11-20	1	N	N	N	N	H	N	N	N	N	N	0	3.6	.1968	.114	.4	18	20944	0	20944	41888	Y2,1
	2	N	N	N	N	N	H	N	N	N	N	0	3.6	.1968	.114	.4	18	26077	0	10195	36272	Y2,2
21-30	1	N	N	N	H	N	N	N	N	N	H	0	3.6	.1968	.114	.4	18	20944	20944	0	41888	Y3,1
	2	N	N	N	N	H	N	N	N	N	N	0	3.6	.1968	.114	.4	18	26077	0	20944	47021	Y3,2
31-40	1	N	N	H	N	N	N	N	N	H	N	0	3.6	.1968	.114	.4	18	20944	20944	1370	43258	Y4,1
	2	N	N	N	H	N	N	N	N	N	H	0	3.6	.1968	.114	.4	18	26077	20944	0	47021	Y4,2
41-50	1	N	H	N	N	N	N	N	H	N	N	0	3.6	.1968	.114	.4	18	20944	20944	5271	47159	Y5,1
	2	N	N	H	N	N	N	N	N	H	N	0	3.6	.1968	.114	.4	18	26077	20944	1370	48391	Y5,2
51-60	1	H	N	N	N	N	N	H	N	N	N	0	5.4	.1992	.141	.6	25.5	20944	20944	10195	52083	Y6,1
	2	N	H	N	N	N	N	N	H	N	N	0	3.8	.2064	.134	.4	18	26077	20944	5271	52292	Y6,2
61-70	1	N	N	H	N	N	N	N	N	H	N	80	3.8	.2064	.134	.4	18	34836	20944	1370	57150	Y7,1
	2	N	H	N	N	N	N	N	H	N	N	80	3.8	.2064	.134	.4	18	30757	20944	5271	56972	Y7,2
71-80	1	H	N	N	N	N	N	H	N	N	N	0	5.4	.1992	.141	.6	25.5	30757	20944	10195	61716	Y8,1
	2	N	H	N	N	N	N	N	H	N	N	0	3.8	.2064	.134	.4	18	34836	20944	5271	61051	Y8,2
81-90	1	H	N	N	N	N	N	H	N	N	N	80	5.4	.1992	.141	.6	25.5	34836	20944	10195	65975	Y9,1
	2	N	N	N	H	N	N	N	N	N	H	80	4.5	.2104	.078	.65	25.5	38196	20944	0	59140	Y9,2
91-100	1	H	N	N	N	N	N	H	N	N	N	80	6.4	.2068	.135	.85	31.5	34836	20944	10195	65975	Y10,1
	2	N	N	H	N	N	N	N	N	H	N	80	3.8	.2064	.134	.4	18	34196	20944	1370	60510	Y10,2
100+	1	H	N	N	N	N	H	N	N	N	N	80	3.8	.2064	.134	.4	18	38196	20944	15556	74696	Y11,1
	2	N	H	N	N	N	N	H	N	N	N	80	3.8	.2064	.134	.4	18	38196	20944	10195	69335	Y11,2

H = Harvest

N = No harvest

The objectives of management are to: a) minimize timber volume harvested from the forest, b) maximize the number of indicator species existing in the area, and c) control (i.e., minimize) the production of porcupines. Resource constraints which must be satisfied include: a) acreage of forest land by age class and b) nondeclining timber harvest policy imposed on a decadal basis.

The major question facing the land manager is how to allocate the forest land base (i.e. acres by age class and species) to each management alternative to best attain the stated objectives. From Tables 3a and 3b, it is evident that not all objectives can be achieved simultaneously. Thus, some trade-offs among objectives are necessary. Furthermore, the large number of possible combinations of assignments of acres to management alternatives suggest the use of a MOP approach to the problem. From the earlier evaluation of MOP techniques the STEP method is selected for this problem.

The calculation phase of the STEP method involves the construction of a pay-off table. This is done by solving (2.3-2.4) for each of the p objective functions. For the case study (2.3-2.4) take on the following form:

$$\left.\begin{array}{l} \text{Max } Z_k \\ \text{for } k = 1, 2, \ldots 7 \\ \text{and } k \neq 5 \\ \\ \text{Min } Z_k \\ \text{for } k = 5 \end{array}\right\} = \sum_{j=1}^{11} \sum_{l=1}^{2} C_{kj} X_{jl} + P_{kj} Y_{jl}$$

subject to

$$\sum_{l=1}^{2} X_{jl} \leq A_j \qquad \text{for } j = 1, 2, \ldots 11$$

$$\sum_{l=1}^{2} Y_{jl} \leq B_j \qquad \text{for } j = 1, 2, \ldots 11$$

$$V_t \geq V_{t-1} \qquad \text{for } t = 1, 2, \ldots 10$$

where

C_{kj} = objective function coefficients denoting amount of timber or number of indicator species produced per acre of land in Douglas-fir managed under alternative 1.

P_{kj} = Same as above except for true fir acres

X_{jl} = Number of areas of Douglas-fir in age class j managed under alternative 1

Y_{jl} = Same as above except for true fir acres

A_j = Total number of acres of Douglas-fir in age class j.

B_j = Same as above except for true fir acres.

V_t = Total board foot harvest volume in period t

This problem involves seven objective functions which are: a) maximize timber harvest volume, (b) maximize wildlife species 1, 2, 3, 5 and 6, and c) minimize wildlife species 4. By solving the above formulation sequentially for each objective function the pay-off table shown in Table 4 is constructed. The ideal solution is given by the solutions corresponding to the diagonal elements of Table 4. Obviously, however, this solution is infeasible. Thus, a compromise solution must be determined.

Table 4. Pay-off Table for Case Study

Objective Function	Timber Vol (bd. ft.)	Numbers of Animals					
		Species 1	Species 2	Species 3	Species 4	Species 5	Species 6
1	12,908,376,334	3,602,220	1,237,496	34,570	16,790	67,188	4,738,900
2	12,130,183,780	4,453,062	1,169,030	33,206	17,842	75,157	4,613,863
3	12,807,385,660	3,192,900	1,256,480	34,558	18,531	69,917	4,718,370
4	12,838,996,140	3,439,300	1,243,795	34,994	21,883	69,864	4,661,888
5	11,452,860,300	3,139,120	1,216,729	31,710	16,250	65,541	4,600,726
6	12,389,625,800	4,007,820	1,754,320	33,076	17,832	76,935	4,628,361
7	12,327,823,070	2,848,200	1,231,166	33,679	17,961	67,234	4,784,175

Two weighing approaches are considered in deriving compromise solutions. The first approach involves the use of calculated weights (2.9-2.10) wherein the weights are a function of the difference between the ideal solution and the compromise solution. Eq. (2.10) is slightly modified by omitting term 2. The second approach utilizes an equal weighing of all objectives. Before calculating any compromise solution, all objective function coefficients are scaled to comparable magnitudes.

Summary of Results

Table 5 describes a summary of three compromise solutions derived using calculated weights. From the pay-off table (Table 4) and using (2.9 and 2.10, modified) a set weights are calculated as shown below:

Objective Function	α_k	w_k
1. Timber Vol.	0.112575	0.102
2. Species 1	0.29506	0.267
3. Species 2	0.06959	0.063
4. Species 3	0.09384	0.084
5. Species 4	0.34660	0.314
6. Species 5	0.14810	0.134
7. Species 6	0.0383	0.034
	1.10406	

These weights are included in (2.6-2.8) and are used to derive the first compromise solution as shown in Table 5. The percent difference between the maximum (minimum) value and that produced by the compromise solutions are also shown in Table 5.

Table 5. Summary of Compromise Solutions with Calculated Weights

Objective Function	Maximum/ Minimum	First Compromise	% Diff. from Maximum	Second Compromise	% Diff. from Maximum	Third Compromise
T.Vol. (bd. ft.)	12,908,376,234	12,378,534,003	4.02	12,417,960,263	3.79	12,418,243,130
Species 1	4,453,062	4,305,688	3.31	4,274,939	4.00	4,274,939
Species 2	1,256,480	1,170,475	6.84	1,176,876	6.33	1,176,976
Species 3	34,994	32,334	7.60	33,558	4.10	33,558
Species 4	16,250	17,504	7.16	17,777	8.5	17,774
Species 5	76,935	74,313	3.41	75,757	1.5	74,045
Species 6	4,784,175	4,580,609	4.25	4,607,763	3.68	4,607,740

From Table 5, it is judged that current attainment levels for indicator species 1 and 5 are acceptable and that a four percent relaxation from these levels is permissible. This reduction then allows the reallocation of resources to better attain remaining objectives.

Following a recalculation of weights (w_k) the problem expressed in (2.6-2.8) is again solved to obtain the second compromise solution shown in Table 5. At this point it is judged that species 2 and 4 are not being produced at satisfactory levels. In order to free up additional resources, the current attainment levels for the following objectives are reduced: (a) timber volume and (b) indicator species 1, 3, 5 and 6. After computing new weights, eqs. (2.6-2.8) are solved and a third compromise is obtained (Table 5). At this point, the solution is judged to be the best compromise available and the procedure is completed.

For comparison, a second set of compromise solutions is sought by using equally weighted objectives. A process similar to that used for calculated weights is employed. The attainment levels for each objective function are shown in Table 6. A comparison of the third compromise solution shown in Tables 5 and 6 reveals that the method of equal weights provides better attainment levels for five of the seven objectives. However, the attainment levels for all seven objectives are very close to one another. Thus, it appears that either weighing method produces comparable results for this problem.

Table 6. Summary of Compromise Solutions with Equal Weights

Objective Function	Maximum/ Minimum	First Compromise	% Diff. from Maximum	Second Compromise	% Diff. from Maximum	Third Compromise
T.Vol. (bd. ft.)	12,908,376,234	12,435,212,170	3.66	12,435,121,170	3.66	12,435,121,170
Species 1	4,453,062	4,295,302	2.54	4,274,939	4.0	4,274,939
Species 2	1,256,480	1,184,655	5.72	1,184,655	5.72	1,185,311
Species 3	34,994	33,416	4.51	33,450	4.51	33,450
Species 4	16,250	17,827	9.7	17,793	8.67	17,930
Species 5	76,935	74,515	3.14	74,751	2.83	74,688
Species 6	4,784,175	4,644,753	2.91	4,637,530	3.1	4,639,916

Summary

In this paper, different MOP techniques under three general approaches are described and evaluated. Of the three methods, the interactive approach is favored as a better alternative for analyzing forest land management planning problems. Among the interactive approaches, the STEP is judged as the most appropriate for land use planning because of its computational efficiency and simpler algorithmic procedure. Its main disadvantage is its inability to generate explicit trade-off information. A case study illustrates the conceptual implementation of STEP.

Bare and Kitto [3] 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 optimal 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 [10], [27]. Brill [10] advocates the joint use of simulation and optimization models to address these problems. This approach may be useful in forest land use planning where the combination of two or more models can offer a better perspective of the land management planning problem.

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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