Resolving multiple goal conflicts with interactive goal programming

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A two-phase interactive goal programming procedure is described, which is potentially useful for resolving multiple-use conflicts where multiple and conflicting objectives exist. In the analytical phase, the procedure locates efficient solutions that are proportionally equidistant from the established goal targets. In the decision phase, these results are presented to the decision maker who either accepts the compromise solution provided by the analyst or revises the goal targets and enters into another iteration. The important features of the procedure are (*i*) the decision maker is not required to explicitly specify any weights or utility function to express preference among objectives; (*ii*) the results of each iteration are presented to the decision maker graphically, using value paths to allow easy visualization of the extent of compatibility or conflict among the different objectives; and (*iii*) the analyst explores efficient basic as well as nonbasic solutions in search of the best compromise solution. An illustrative example is included to demonstrate the application of the procedure.

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Cet article décrit un procédé interactif de programmation par objectif en deux phases pouvant servir à résoudre des conflits polyvalents lorsque sont présents des objectifs multiples et conflictuels. Au cours de la phase analytique, le procédé localise les solutions efficaces se situant à équidistance des objectifs préétablis. Au cours de la phase décisive, ces résultats sont présentés au décideur qui peut soit accepter la solution de compromis suggérée par l'analyste, soit réviser les objectifs et poursuivre une autre intéraction. Les principaux aspects du procédé sont les suivants : (*i*) le décideur n'a pas spécifier une pondération ou une fonction utilitaire quelconque pour exprimer sa préférence d'un objectif en particulier ; (*ii*) les résultats de chaque itération sont présentés au décideur sur graphiques, au moyen de trajectoires qui permettent de visualiser avec facilité le degré de compatibilité ou de conflit parmi les divers objectifs ; et (*iii*) l'analyse explore les diverses solutions efficaces, élémentaires ou non, en vue de rechercher le meilleur compromis. L'article renferme un exemple, à titre d'illustration, pour bien montrer l'application qu'on peut faire de ce procédé.

[Traduit par la revue]

Introduction

Multiple-use forest planning problems are often characterized by conflicts among several incompatible objectives that are to be optimized simultaneously. To aid forest planners and decision makers in such environments, a variety of multiobjective programming models have been developed. In forestry, the most popular of these models is goal programming (Field 1973; Bell 1976; Rustagi 1976, 1985; Bare and Anholt 1976; Porterfield 1976; Dane et al. 1977; Schuler et al. 1977; Hansen 1977; Dyer et al. 1979; Field et al. 1980; Kao and Brodie 1979; Mitchell and Bare 1981; Hotvedt et al. 1982; Arp and Lavigne 1982; Walker 1985; Mendoza 1986). Other multiobjective programming methods applied to forestry problems are those of Bertier and deMontgolfier (1974), Steuer and Schuler (1978), de Kluyver et al. (1980), Mattheiss and Land (1984), Allen (1986), Harrison and Rosenthal (1986), Hallefjord et al. (1986), Glover and Martinson (1987), Mendoza et al. (1987), and Bare and Mendoza (1987).

Although forestry applications of goal programming began to appear in the mid-1970s, other multiobjective programming techniques have been applied only recently. Further, a wide variety of solution methodologies have been utilized in these applications.[1] Yet, despite the many algorithms and approaches advanced to date, no single approach has emerged as "best" for all types of multiobjective programming problems (Ignizio 1983).

Evaluative studies of several interactive multiobjective programming methods have also reached this same conclusion (Wallenius 1975; Reeves and Franz 1985; Gibson et al. 1987). These studies, coupled with our own experience, have led us to conclude that continued research in the development and testing of interactive multiobjective programming methods is warranted.

As previously mentioned, a variety of multiobjective programming techniques have been developed to aid decision makers. Chief among the interactive approaches are algorithms of Benayoun et al. (1971), Geoffrion et al. (1972), Zionts and Wallenius (1976, 1983), Steuer (1976), Steuer and Choo (1983), and Evren (1987). In addition, interactive goal programming algorithms have been developed by Dyer (1972), Franz (1980), Masud and Hwang (1981), and Ignizio (1981). These latter methods all attempt to progressively articulate the preferences of the decision maker by adjusting the target levels, weights, and (or) rankings assigned to the deviational variables. However, different solution techniques are used to implement the algorithms. Korhonen and Laakso (1986) present an interactive multiobjective programming method that has some features of our model, but does not utilize goal programming.

In this paper we describe and illustrate an interactive goal programming algorithm that relies on the progressive revision of aspiration (target) levels as alternate feasible solutions are presented graphically to the decision maker. Special features of the method are the examination of efficient basic as well as nonbasic solutions and manipulation of the weights by the analyst to force the solution in a direction specified by the

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[1]For more information on multiobjective programming techniques see Lee 1972, Cochrane and Zeleny 1973, Zeleny 1974, Haimes et al. 1975, Zeleny 1976, Thiriez and Zionts 1978, Starr and Zeleny 1977, Cohon 1978, Zionts 1978, Hwang and Masud 1979, Fandel and Gal 1980, Raff and Zeleny 1980, Rietveld 1980, Morse 1981, Ignizio 1982, Zeleny 1982, Chankong and Haimes 1983, Evans 1984, Gal 1986, and Romero 1986.

decision maker. Explicit identification of weights by the decision maker, however, is not required. This contrasts with many goal programming algorithms where manipulation of the weights by the decision maker plays a pivotal role.

Throughout this paper we adopt Ignizio's (1983) terminology: (*i*) *objectives* are represented by mathematical functions of the decision variables; (*ii*) *aspiration* or *target levels* refer to a specific value associated with a desired level of achievement of an objective and are used to measure the achievement or nonachievement of an objective; (*iii*) *goals* refer to an objective in conjunction with an aspiration level; and (*iv*) *constraints* take on the same mathematical appearance as goals but must be rigidly observed. Thus, constraints are absolute goals that must be satisfied to ensure feasibility.

Linear multiobjective programming

A linear multiobjective programming problem may be formulated as

maximize

$$c^k x \qquad \text{for all } k = 1, 2, 3, \ldots, p$$

subject to

$$Ax \leqq b$$

$$x \geqq 0$$

where x is an n-dimensional column vector of decision variables (including slack and surplus variables); c^k is a vector of coefficients for the kth objective; A is an $m \times n$ matrix of input/output coefficients; and b is an m-dimensional column vector of constraint limits.

When faced with a multiple objective situation, the concept of optimality, as used in single objective optimization, does not apply. Instead, all feasible solutions are separated into two mutually exclusive sets: (*i*) efficient (nondominated); and (*ii*) inefficient (dominated) solutions. Efficient solutions have the property that an improvement in the attainment of one or more of the objectives is only possible by decreasing the achievement of at least one of the remaining objectives. Because there are usually many efficient solutions to choose from, the decision maker must articulate a set of preferences that express value judgments relating the importance of each identified objective. Given these preferences, the decision maker selects a solution that best meets the stated goals. Because of incompatibility among objectives it is usually impossible to attain all goals simultaneously. Thus, the decision maker chooses the best compromise solution from the identified efficient solutions.

The size of the efficient set depends on two things: (*i*) the degree of conflict or incompatibility among objectives; and (*ii*) the shape of the feasible region. Everything else remaining constant, for compatible objectives, the efficient region may be confined to a small part of the feasible region but increases with the increase in conflict among various objectives. If the objectives are in complete conflict, the efficient region covers the entire feasible region (including the interior).

The two-phase interactive goal programming method proposed in this paper consists of *analytical* and *decision* phases. Given the decision maker's target level for each objective, the analytical phase begins with the analyst finding an efficient solution that is proportionally equidistant from each goal tar-

get.[2] This solution is presented to the decision maker in a graphical form depicting the targets for each goal and their attainment levels. We utilize the concept of *value paths* (Cohon 1978) to help the decision maker visualize these relationships. Either the decision maker accepts this solution as the best compromise, or revises the goal targets to make them more realistic.

Any goal target that is set at a level higher than that achieved by the equidistant solution implies that the attainment of other goals must be reduced if this goal target is to be reached. Using interactive goal programming, the analyst reformulates the problem and checks on the attainability of these targets. If they are unattainable, a nonbasic solution, close to the goal targets, is produced and the results are presented to the decision maker graphically. The goal targets are then revised by the decision maker in light of the analyst's findings. The interaction between the decision maker and the analyst continues until the decision maker's modified goal targets become attainable or the solution from the last iteration is accepted as the best compromise solution.

During the analytical phase, the search for the best compromise solution is not limited to the efficient basic set but is extended to the entire efficient surface, including nonbasic solutions.[3] This is accomplished by introducing additional goals with different target levels for each objective of interest.

At no time is the decision maker either swamped by a massive amount of data or required to understand and interpret technical information. Instead, to help undertake an informed revision of the goal targets, the analyst provides the decision maker with a graphical display of desirable goals and feasible levels from the previous solutions. Especially important is the fact that the decision maker is not asked to specify any weights or utility function.

Interactive goal programming formulation

Unlike conventional goal programming, in which the decision maker is required to specify target levels, weights, and, in some cases, preemptive priorities, our method only requires the decision maker to specify and revise target levels for each objective after the analyst has provided sufficient information to make an informed decision. Another difference is that more than one goal is formulated for each objective. As mentioned, this is done to provide the capability to generate nonbasic solutions.[3] We suggest two to five of these additional goals for each objective, but their number is best left to the discretion of the analyst.

In the initial analytical phase, the analyst solves p simple linear programming problems to determine the upper (Z^{k*}) and lower (z^{kl}) value for each objective by maximizing each objective individually and examining the objective function value of the remaining objectives. This is done without any input from the decision maker with respect to target levels, weights, and (or) priorities. These values serve two purposes. First, they provide reference points for each objective, which are used by the decision maker to initialize or revise target levels. Second, the inverse of the range ($Z^{k*} - z^{kl}$) provides a set of relative

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[2]Equidistant solutions are recommended because they provide the maximum simultaneous attainment level for all goals and they illustrate the degree of conflict among goals.

[3]While these are basic solutions for the expanded goal programming formulation, they are nonbasic in terms of the original goal set.

weights which the analyst uses in the initial goal programming solution.

The proposed goal programming formulation of the multi-objective decision problem is

minimize

$$\Sigma_k \Sigma_j (w_j^k \times d_j^{k-})$$

subject to

$$Ax \leqq b$$

$$c^k x + d_j^{k-} - d_j^{k+} = g_j^k$$

$$x \geqq 0, \qquad d_j^{k-} \geqq 0, \qquad d_j^{k+} \geqq 0$$

where w_j^k are the Archimedean weights, d_j^{k-} and d_j^{k+} are negative and positive deviational variables, respectively, and g_j^k are the target levels associated with the jth level of the kth objective. The simplex algorithm guarantees that at most only one of the two deviational variables d_j^{k-} and d_j^{k+} will be in any basic solution.

We utilize Archimedean weights exclusively in our model, but we do not normalize or scale the objective functions. Following Gass (1987), who differs with Hannan (1986), we believe that there is no need to normalize the objective function coefficients because the norm is just part of the weight. It is the calculation of the weights by the analyst (when deriving equidistant solutions) that is characteristic of our proposed procedure.

If g^k is the target level specified by the decision maker for the kth objective, the analyst computes g_j^k as

$$g_j^k = g^k - (j - 1)o^k$$

where o^k is an interval arbitrarily fixed by the analyst. As pointed out earlier, this is done to generate nonbasic solutions in the proximity of the decision maker's target levels.

The analyst uses Z^{k*} as g^k in the initial formulation and by suitably adjusting the interval o^k along with the weights, obtains an efficient solution that is situated approximately at the same relative distance between Z^{k*} and z^{k1}. This solution serves two purposes. First, the relative position tells the analyst something about the degree of conflict among different objectives. Generally, the greater the degree of conflict, the closer the relative solution values will be to $1/p$ times the range $(Z^{k*} - z^{k1})$. Second, this solution serves as a benchmark for the decision maker in deciding upon realistic goal levels to use in the next iteration.

In the decision phase, the results of the initial goal programming run are presented to the decision maker in the form of a value graph where the range $(Z^{k*} - z^{k1})$ is shown along with the relative position of the achieved level of each objective. Based on this information the decision maker is required to specify the target level for each objective. If the decision maker is satisfied with the proposed solution provided by the analyst, the process stops. If not, the decision maker proposes new target levels.

Armed with the revised goal targets, the analyst initiates another analytical phase involving the reformulation and solution of a goal programming problem. Three possible outcomes can occur when this goal programming formulation is solved. (*i*) The decision maker's target levels are unachievable. In this case the analyst finds a feasible solution which is closest to the goals. (*ii*) The decision maker's goals are attainable, but the solution is not efficient. In this case the analyst identifies an efficient solution that improves at least one of the objectives.

(*iii*) The solution attains all target levels and is efficient. The best compromise solution has been identified.

In the case of *i* or *ii*, the decision maker may wish to revise the goal targets leading to another iteration of the process. This continues until the decision maker's target levels and the attained levels more or less coincide. For a rational decision maker, this should not take more than four or five cycles.

An example

A simple linear multiobjective problem is presented to illustrate how the process works. This problem involves two constraints and three objectives that are to be maximized:

maximize

$$Z_1 = 10X_1 + 13X_3$$

$$Z_2 = X_1 + 6X_2$$

$$Z_3 = 40X_1 + 25X_2 + 15X_3$$

subject to

$$X_1 + X_2 + X_3 \leqq 100$$

$$25X_1 + 72X_2 + 45X_3 \leqq 5000$$

$$X_1, X_2, X_3 \geqq 0$$

Table 1 contains an abbreviated payoff table summarizing the maximum and the minimum value for each objective when the objectives are maximized one at a time. The range of objective function values and the approximate relative weights used to generate the initial goal programming solution are also given. The attainment levels of different objectives when each objective is maximized individually are shown in Fig. 1. For example, when maximizing objective 3, objectives 1 and 2 take on values of 1000 and 100 units, respectively. From Fig. 1 it is clear that objectives 1 and 2 are in total conflict while objective 3 is quite compatible with objective 1 but only weakly compatible with objective 2.

The goal programming formulation of the original multiobjective problem during the initial analytical phase is

minimize

$$2d_1^{1-} + 4d_2^{1-} + 6d_3^{1-} + 8d_4^{1-} + 10d_5^{1-} + 6d_1^{2-}$$
$$+ 12d_2^{2-} + 18d_3^{2-} + 24d_4^{2-} + 30d_5^{2-} + d_1^{3-} + 2d_2^{3-}$$
$$+ 3d_3^{3-} + 4d_4^{3-} + 5d_5^{3-}$$

subject to

$$X_1 + X_2 + X_3 \leqq 100$$

$$25X_1 + 72X_2 + 45X_3 \leqq 5000$$

$$10X_1 + 13X_3 + d_1^{1-} - d_1^{1+} = 1300$$

$$10X_1 + 13X_3 + d_2^{1-} - d_2^{1+} = 1100$$

$$10X_1 + 13X_3 + d_3^{1-} - d_3^{1+} = 900$$

$$10X_1 + 13X_3 + d_4^{1-} - d_4^{1+} = 700$$

$$10X_1 + 13X_3 + d_5^{1-} - d_5^{1+} = 500$$

$$X_1 + 6X_2 + d_1^{2-} - d_1^{2+} = 420$$

$$X_1 + 6X_2 + d_2^{2-} - d_2^{2+} = 355$$

$$X_1 + 6X_2 + d_3^{2-} - d_3^{2+} = 290$$

$$X_1 + 6X_2 + d_4^{2-} - d_4^{2+} = 225$$

$$X_1 + 6X_2 + d_5^{2-} - d_5^{2+} = 160$$

$$40X_1 + 25X_2 + 15X_3 + d_1^{3-} - d_1^{3+} = 4000$$

$$40X_1 + 25X_2 + 15X_3 + d_2^{3-} - d_2^{3+} = 3550$$

$$40X_1 + 25X_2 + 15X_3 + d_3^{3-} - d_3^{3+} = 3100$$

$$40X_1 + 25X_2 + 15X_3 + d_4^{3-} - d_4^{3+} = 2650$$

$$40X_1 + 25X_2 + 15X_3 + d_5^{3-} - d_5^{3+} = 2200$$

In the initial goal programming formulation, five goals are created for each objective with a fairly wide range of target levels. This is done (*i*) to allow consideration of nonbasic solutions as the best compromise solution; and (*ii*) to make allowance for the conflict that may exist between different objectives. The weights assigned to the deviational variables associated with the multiple goals for each objective are progressively larger for smaller target levels. The objective is to obtain solution values for different objectives at approximately the same proportional distance from the target levels (see footnote 2).

The following solution values for the initial goal programming formulation are obtained using a standard LP computer program:

$$Z_1 = 660; \qquad Z_2 = 270; \qquad Z_3 = 3490$$
$$X_1 = 66; \qquad X_2 = 34; \qquad X_3 = 0$$

The upward sloping line in Fig. 2 displays this solution and illustrates several important features. First, proportional departures from the three goal targets are not achieved using the Archimedean weights incorporated into the present goal programming model. This implies that the objective function vectors are not orthogonal.[4] Further, it implies that the weights and (or) target levels need to be manipulated (by the analyst) if proportional departures are to be achieved. Second, the solution indicates that the three objectives are not in total conflict. This is illustrated by the percent departures of 51, 65, and 80%, respectively, which measure deviations as a percent of the maximum value for each objective over the range ($Z^{k*} - z^{k1}$). If the three goals are in total conflict, percent departures are expected to be close to 33% of the range.

To produce an equidistant solution, it is necessary for the analyst to further manipulate the weights and (or) target levels. After repeated experimentation, the following goal programming model involving four goals per objective is developed:

minimize

$$7d_1^{1-} + 10.5d_2^{1-} + 14d_3^{1-} + 17.5d_4^{1-} + 8d_1^{2-} + 12d_2^{2-}$$
$$+ 16d_3^{2-} + 20d_4^{2-} + 0.2d_1^{3-} + 0.4d_2^{3-} + 0.6d_3^{3-}$$
$$+ 0.8d_4^{3-}$$

subject to

$$X_1 + X_2 + X_3 \leq 100$$

$$25X_1 + 72X_2 + 45X_3 \leq 5000$$

$$10X_1 + 13X_3 + d_1^{1-} - d_1^{1+} = 800$$

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[4]Objective function vectors are orthogonal if their scalar product vanishes. If not orthogonal, the weights (w_j^k) do not serve their intended purpose.

TABLE 1. Abbreviated pay-off table for sample problem

Objective	Max.	Min.	Range	Rel. wt.*
Z_1	1300	0	1300	2
Z_2	417	0	417	6
Z_3	4000	1500	2500	1

*The relative weights are approximately proportional to the inverse of the range of the attained levels for each objective. For example, for Z_2 we have $(1/417) \times 2500 = 6$.
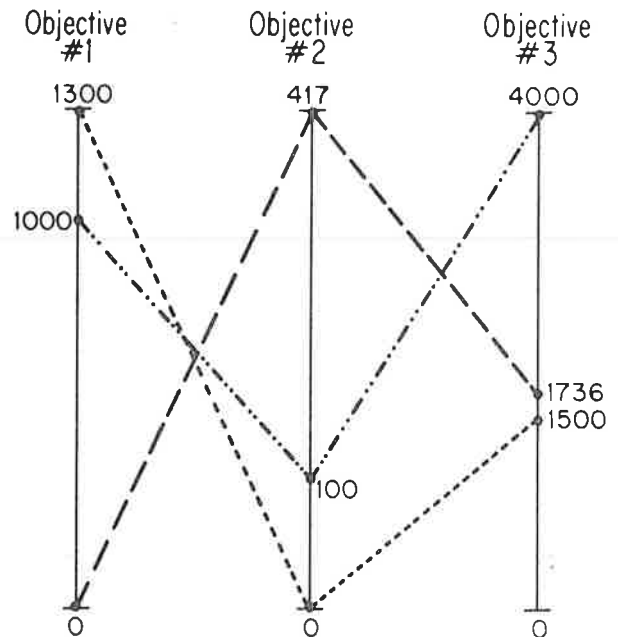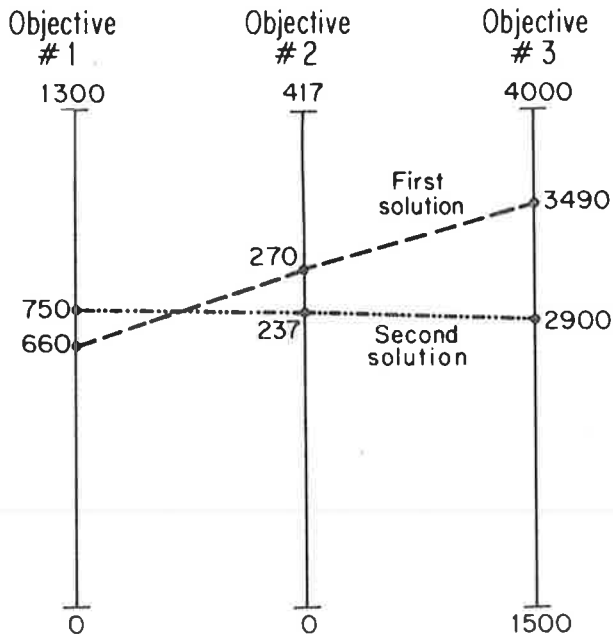

FIG. 1. Attainment levels of the three objectives when each objective is maximized individually.

$$10X_1 + 13X_3 + d_2^{1-} - d_2^{1+} = 750$$

$$10X_1 + 13X_3 + d_3^{1-} - d_3^{1+} = 700$$

$$10X_1 + 13X_3 + d_4^{1-} - d_4^{1+} = 650$$

$$X_1 + 6X_2 + d_1^{2-} - d_1^{2+} = 280$$

$$X_1 + 6X_2 + d_2^{2-} - d_2^{2+} = 265$$

$$X_1 + 6X_2 + d_3^{2-} - d_3^{2+} = 250$$

$$X_1 + 6X_2 + d_4^{2-} - d_4^{2+} = 235$$

$$40X_1 + 25X_2 + 15X_3 + d_1^{3-} - d_1^{3+} = 3100$$

$$40X_1 + 25X_2 + 15X_3 + d_2^{3-} - d_2^{3+} = 3000$$

$$40X_1 + 25X_2 + 15X_3 + d_3^{3-} - d_3^{3+} = 2900$$

$$40X_1 + 25X_2 + 15X_3 + d_4^{3-} - d_4^{3+} = 2800$$

The corresponding solution values are

$$Z_1 = 750; \qquad Z_2 = 237.3; \qquad Z_3 = 2900;$$
$$X_1 = 43.0; \qquad X_2 = 32.4; \qquad X_3 = 24.6$$

This solution is displayed in Fig. 2 as a horizontal line, with associated percent departures of 58, 57, and 56%, respectively, which measure deviations as a percent of the maximum value over the range ($Z_k^* - z^{k1}$). The Archimedean weights and target levels required to produce this equidistant solution are

FIG. 2. Attainment levels of the three objectives in the first iteration of the analytical phase.

FIG. 3. Goal targets and corresponding attainment levels for the three objectives in the revised formulation.

dramatically different from those used in the first goal programming formulation. Although an equidistant solution is shown, the percent departures are not one third of the range. Thus, it is clear that the three objectives have some degree of compatibility. The horizontal line further indicates the maximum level of achievement that can be expected for the three goals when considered simultaneously.

Figures 1 and 2 provide sufficient information to enable the decision maker to specify realistic goal levels for the next iteration, thus completing the initial analytical phase. At no time has the decision maker been asked to specify weights associated with deviational variables, thus avoiding this aspect of many goal programming algorithms.

Suppose that after deliberation, the decision maker suggests goal levels of 800, 250, and 3600, respectively, for the three objectives. After manipulation of the weights, the number of goals and their target levels, and with the aim of more or less proportional departures from these goals, the analyst formulates the following problem:

minimize

$$7d_1^{1-} + 10.5d_2^{1-} + 6d_1^{2-} + 12d_2^{2-} + d_1^{3-} + 2d_2^{3-}$$

subject to

$$X_1 + X_2 + X_3 \leqq 100$$

$$25X_1 + 72X_2 + 45X_3 \leqq 5000$$

$$10X_1 + 13X_3 + d_1^{1-} - d_1^{1+} = 800$$

$$10X_1 + 13X_3 + d_2^{1-} - d_2^{1+} = 750$$

$$X_1 + 6X_2 + d_1^{2-} - d_1^{2+} = 250$$

$$X_1 + 6X_2 + d_2^{2-} - d_2^{2+} = 235$$

$$40X_1 + 25X_2 + 15X_3 + d_1^{3-} - d_1^{3+} = 3600$$

$$40X_1 + 25X_2 + 15X_3 + d_2^{3-} - d_2^{3+} = 3500$$
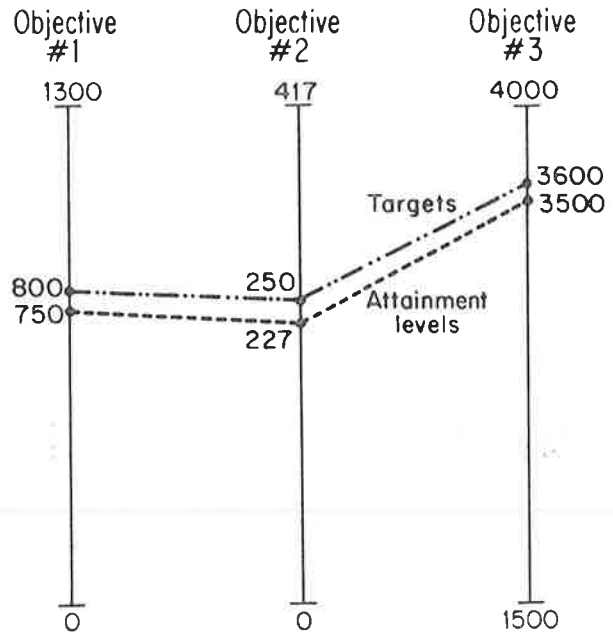
The corresponding solution values are

$$Z_1 = 750; \quad Z_2 = 227; \quad Z_3 = 3500;$$

$$X_1 = 69.5; \quad X_2 = 26.3; \quad X_3 = 4.2$$

Comparing this solution (see Fig. 3) with the previous solution, where proportionally equidistant levels of attainment are realized, shows that the achievement of objective 1 remains at 750 units, objective 2 has decreased 10 units, and objective 3 has increased 600 units. The decision maker must decide if this solution is superior to the previously displayed solution. With all goals given equal importance as effected by attempting to achieve proportionally equidistant deviations, the analyst has provided sufficient information to enable the decision maker to revise target levels if this is deemed necessary.

As is obvious from the above formulation, the analyst is free to use any number of goals, any convenient step size, and any weights for the purpose of ensuring more or less proportional departures from the stated targets. Further, the decision maker may choose not to try to attain proportional deviations from target levels, in which case the analyst can produce other compromise solutions for evaluation.

It should be clear that other combinations of weights and (or) target levels for the goals may lead to a different solution. However, such solutions will not depart significantly from the above solution as long as the analyst uses the same criterion of distance from the stated goals.

At this point in the analysis the decision maker should have a good understanding of realistic target levels and the implicit trade-off among objectives. Thus, the search process can be terminated by accepting one of the solutions proposed by the analyst or the goal targets can be revised and another cycle of analysis can be initiated. A rational decision maker should be able to identify the best compromise solution within four to five iterations, depending on the degree of incompatibility among goals.

Discussion

The interactive goal programming procedure outlined here is a straightforward approach for helping the decision maker

identify the best compromise solution from among all possible efficient solutions. The mechanics of the process are relatively transparent and the decision maker is not asked to specify a preference structure in the form of weights and (or) a ranking of objective functions. Lastly, the graphical presentation of results makes it very easy for the decision maker to better understand the interdependencies and conflicts among objectives and thus be able to adjust goal levels to make them more realistic and attainable. The decision maker still must make a value judgement regarding the combination of levels for different objectives that are ultimately considered acceptable.

In formulating the goal programming problem, the analyst has considerable flexibility as long as solutions are generated that reflect the decision maker's wishes. To some extent the computational burden depends upon how realistic the target levels are and on the degree of conflict among different objectives. The magnitude of the trade-off among objectives is a direct function of the level of conflict.

The salient features of this approach are (i) use of multiple goals for each objective to facilitate the generation of nonbasic solutions, and also allow a more equitable distribution of the shortfalls (from specified targets) among different objectives; (ii) manipulation of weights and target levels for controlling the distribution of the shortfall among different objectives.

A maximum of only five efficient basic solutions are utilized in the example presented here. However, the number of possible efficient solutions, both basic and nonbasic, is infinitely large. In view of the overwhelmingly large number of nonbasic solutions to the problem, it is very likely that the decision maker's preferred solution will also be nonbasic. Therefore, it is imperative that the search procedure be flexible enough to generate both types of efficient solution.

The reporting of results basically duplicates the method proposed by Cohon (1978) and Zeleny (1982). This graphical display of results using value paths shows both the target levels and the most optimistic achievable levels given those targets. This type of display facilitates the decision maker's revision of the targets for the next iteration. Perhaps it will also make it easier for a rational decision maker to accept a less than perfect solution as the best compromise solution.

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