Goal Programming and Its Variants

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INTRODUCTION

Within the realm of multicriteria decision making (MCDM) exists a powerful method for solving problems with multiple objectives. Goal programming (GP) was the first multiple-objective technique presented in the literature (Dowlatshahi, 2001). The premise of GP traces its origin back to a linear programming study on executive compensation in 1955 by Charnes, Cooper, and Ferguson even though the specific name did not appear in publications until the 1961 textbook entitled *Management Models and Industrial Applications of Linear Programming*, also by Charnes and Cooper (Schniederjans, 1995). Initial applications of this new type of modeling technique demonstrated its potential for a variety of applications in numerous different areas. Until the middle of the 1970s, GP applications reported in the literature were few and far between. Since that time, primarily due to influential works by Lee and Ignizio, a noticeable increase of published GP applications and technical improvements has been recognized. The number of case studies, along with the range of fields, to which GP has been and still is being applied is impressive, as shown in surveys by Romero (1991) and Aouni and Kettani (2001). It can be said that GP has been, and still is, the "most widely used multi-criteria decision making technique" (Tamiz, Jones, & Romero, 1998, p. 570).

BACKGROUND

The GP model is a simple extension and modification of the linear programming technique that provides a simultaneous solution of a system of complex objectives rather than a single one (Munhoz & Morabito, 2002).

[It] is a technique used for optimizing problems that have multiple conflicting criteria. In goal programming, each objective is assigned a target level and a relative importance of achieving that target. It then finds an optimal solution that comes as close as possible to the target values. One significant difference between goal programming and other types of modeling is the use of goal constraints in addition to real constraints. A goal constraint is different from a real constraint in that the former is set equal to a target level that does not have to be achieved. With the introduction of deviational variables, the program can still reach a feasible solution without achieving the target level. (Nichols & Ravindran, 2004, p. 323)

GP provides a more satisfactory treatment of a problem where, in many cases, problems can still be solved using standard linear programming algorithms: "The overall objective of goal programming is to minimize the deviations between goal achievement and desired aspiration levels" (Henry & Ravindran, 2005, p. 112).

Two main types of models exist within GP: preemptive and weighted (nonpreemptive). Preemptive programming, also known as lexicographic GP, involves establishing goals in order of importance, from the most important to the least. Then, the objective function is optimized for each goal one at a time. According to Scott, Deckro, and Chrissis (2005, p. 96), "In 1965, Ijiri introduced preemptive priority factors as a way of ranking goals in the objective function of the linear goal programming model and established the assignment of relative weights to goals in the same priority level." Nichols and Ravindran (2004) argued that weighted GP is "similar to preemptive goal programming in that the objective is to minimize the amount of deviation from each specific goal. However, a weight (penalty) is used to quantify how important each goal is with

respect to the other goals, instead of an established hierarchical priority level" (p. 324). Penalty functions were introduced in 1980 by Kvanli, using an interval target rather than a fixed target. These penalties are assessed when over- and/or underdeviations of goal achievement occurs. The objective then is to minimize the total penalties in satisfying the entire model. The idea of penalty functions makes the model more realistic and flexible, and has been applied to many real-world applications (Panda, Banerjee, & Basu, 2005).

After the model has been optimized and goal values have been met, sensitivity analysis can be used to evaluate its effectiveness and identify problem areas. Investigative areas include changes in the weighting of priority levels, changes of the weighting of deviation variables within a given priority level, changes in right-hand-side values, and reordering preemptive priorities.

MAIN FOCUS

Strengths and Weaknesses

Ease and flexibility, a wide variety of uses, and the compatibility of GP with subsequent analysis methods have all been identified as strengths of the modeling technique. GP is an extension of linear mathematical programming and, therefore, is easy to understand and easy to apply. It brings simplicity and ease of use by simultaneously handling a large number of variables, constraints, and objectives. Therefore, the model can be performed over and over again, adjusting the goals, objectives, and weights in order to obtain the decision maker's ideal solution. In this regard, it is a technique similar to both compromise programming and the reference-point methods of problem solving.

GP can also be applied to a large variety of uses from almost any industry and also for global applications. Some of the most common fields involved in the application of GP techniques include agriculture, engineering, financial investment planning, production, natural resources management, land-use planning, and human resources. Specific examples within these fields involve bank asset allocation, employee scheduling, and component production within a supply chain. GP can also be used in combination with other decision-making applications. Also, the two main types of GP themselves can be used in combination. For example,

the user can begin with weighted GP and then double-check the conclusions by running the preemptive GP approach as well.

With all the clear benefits and efficiencies that GP brings, it does not come without some surrounding criticism. The main weakness of GP is the tendency for the solution obtained to be Pareto inefficient. Pareto inefficiencies occur when the achieved level of any one objective can be improved without negatively impacting the achieved level of any other objective. However, this is only a problem if alternative optimum solutions are presented (Caballero & Hernández, 2006). In order to change the inefficient solution to an efficient result, one must first safeguard each objective against degradation by placing upper and lower bounds on the deviational variables. These inefficiencies can be resolved by applying efficiency detection and restoration techniques.

There are three common restoration methods to resolve the issue of Pareto inefficient results when using GP. The first method, straight restoration, simply finds the maximization of the sum of the unweighted deviation variables of the inefficient objectives. The second method, preference-based restoration, finds the sum of the unwanted deviational variables and penalizes these a second time. The third method, interactive restoration, involves the decision maker at this stage, hence the name. He or she chooses the one single inefficient objective that they would like to see become the most improved (Tamiz et al., 1998).

Another criticism or weakness of GP is the challenge of assigning appropriate weights to the objectives. Weights are assigned to the objectives for two purposes. It is often difficult for the decision maker to determine a goal for each objective, causing inaccuracies in the input and therefore in the results. The first purpose is to normalize the goals and the second one is to indicate the decision makers' preferences with respect to each goal. One way this can be controlled is by using the analytic hierarchy principle (AHP) or analytic network principle (ANP). This method determines weights by a pair-wise comparison. Another method of assigning appropriate weights is that of a totally interactive approach by the decision maker. This reflects back to one of the strengths of GP. One of the benefits is ease of use, which enables the user to run the model repeatedly, making adjustments to the goals, objectives, weights, and so forth as he or she goes along. This is where the decision maker would be involved. The user can run the

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