A review of Goal Programming and its applications

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This paper presents a review of the current literature on the branch of multi-criteria decision modelling known as Goal Programming (GP). The result of our indepth investigations of the two main GP methods, lexicographic and weighted GP together with their distinct application areas is reported. Some guidelines to the scope of GP as an application tool are given and methods of determining which problem areas are best suited to the different GP approaches are proposed. The correlation between the method of assigning weights and priorities and the standard of the results is also ascertained.

Keywords: Goal Programming, lexicographic, weighted.

1. Introduction

Goal Programming is a branch of multi-criteria decision analysis. It was first introduced by Charnes et al. in 1955 [9], more explicitly defined by the same authors in 1961 [10], and further developed by Ijiri [33] during the 1960's. The first books dedicated to GP by Lee [46] and Ignizio [29] appeared during the early to mid 1970's.

In the 1970's, GP and its variants were applied to many different subject areas. These included academic resource planning [1,35], accounting [39], agricultural planning [69], energy forecasting [63], portfolio management [46,40], water resource planning [14], library management [25], and media scheduling [18].

Questions were raised as to the effectiveness of GP as an application tool by Zeleny [70] and Harrald [27] during the late 1970's and early 1980's, but GP still grew in popularity judging by the increase of papers applying GP during that period. Figure 1 shows the number of papers on the subject of GP applications during the period 1955–1988. The bibliography used for our survey is contained in the final chapter of Romero [60].

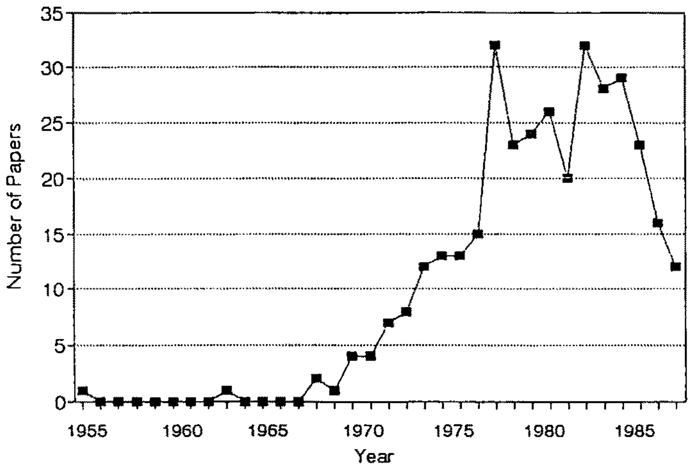

Figure 1. GP application papers per year during the period 1955–1988.

The results show a continuing healthy interest in GP, although slightly less than when the subject became very popular in the late 1970's to early 1980's. Among the application areas utilised or extended in the past ten years are farm growth planning [21], diet planning [45,57], locational analysis [53,41], academic resource planning [24,20], manpower planning [22], police scheduling [62], portfolio analysis [49], interest rate models [6], engineering [30], manufacturing [58], and crew scheduling [56,16].

With the onset of powerful computers, sophisticated algorithms have been developed by Ignizio [31], Schniederjans and Kwak [64], and others [5,47,50]. Olson [59] compares computational time for four GP algorithms and demonstrates the benefits of using Revised-Simplex and Primal-Dual algorithms to solve GP problems. These have made solutions to large-scale GP problems possible, and several papers have been published exploiting this [22,62,23]. Work has also continued into special-case GP algorithms: Integer, Zero–One, Fuzzy, Interactive, and Chance-Constrained. A breakdown of publications in these areas is given in Romero [60]. In total, he lists 355 papers dealing with GP applications in 26 distinct areas.

Research has been done to apply other Multi-Criteria and Management Science techniques to Goal Programming. These include interactive multi-criteria methods [52], "Delphi" techniques [37,38], Saaty's [61] analytical hierarchy approach [23,20,37], and resource planning and management systems (RPMS) networks [66]. Recently, papers have been published dealing with some of the perceived "errors" in GP [60,38,54], and explaining how these can be avoided by the correct setting of weights, goals, priority levels, etc.

The remainder of this paper will be divided into four sections. Section 2 will deal with lexicographic (pre-emptive) GP, section 3 with weighted GP (non-pre-emptive), section 4 with the connection between utility functions and GP. Finally, section 5 will draw conclusions as to the current direction of GP and the direction of the authors' future research. A graphical summary of the inter-relation of Goal Programming topics mentioned in this paper is given in figure 2.

2. Lexicographic GP

Of the 355 papers mentioned by Romero [60], 226 use the concept of Lexicographic GP (LGP), which requires the pre-emptive ordering of priority levels. The standard LGP model can be algebraically represented as

$$\text{Lex min } \boldsymbol{a} = (g_1(\boldsymbol{n},\boldsymbol{p}), g_2(\boldsymbol{n},\boldsymbol{p}),\ldots, g_K(\boldsymbol{n},\boldsymbol{p}))$$

subject to

$$f_i(\boldsymbol{x}) + n_i - p_i = b_i, \quad i = 1,\ldots,m.$$

The model has K priority levels and m objectives. $\boldsymbol{a}$ is an ordered vector of these K priority levels. n_i and p_i are deviational variables which represent the under- and over-achievement of the ith goal, respectively. $\boldsymbol{x}$ is the set of decision variables to be determined. A standard "g" (within priority level) function is given by

$$g_k(\boldsymbol{n},\boldsymbol{p}) = \alpha_{k_1} n_1 + \ldots + \alpha_{k_m} n_m + \beta_{k_1} p_1 + \ldots + \beta_{k_m} p_m.$$

2.1. LEXICOGRAPHIC ALGORITHMS

The first algorithm for solving a lexicographic GP was presented by Charnes and Cooper in their 1961 book [10]. This used a modified version of the two-phase simplex method. The first recorded computer code to implement this method was produced by Jääskeläinen [34] in 1969. This code was, however, inefficient and could only deal with small problems (fewer than 50 variables).

The next stage of LGP algorithms treated each priority level as a separate LP and solved accordingly. Extra constraints were added, to make sure the higher priority level optimal solutions were not denegrated, at each priority level. These were known as sequential simplex algorithms and allowed the solution of medium-scale models. A textbook description of the theory of the sequential simplex method is given in Ignizio [32].

The next attempts to exploit the lexicographic structure were made by Arthur and Ravindran [5], who suggested considering only the constraints relevant to each priority level at that level. Schniederjans and Kwak then produced a dual simplex based method which can eliminate up to half of the deviational variables [64]. A good comparison of these methods as compared with the sequential simplex (conventional and revised) method of solving is found in Olson [59]. Ignizio then introduced a sophisticated primal-dual method of solution based on his work on the development of the multi-dimensional dual [31]. This method allows for the dropping of constraints

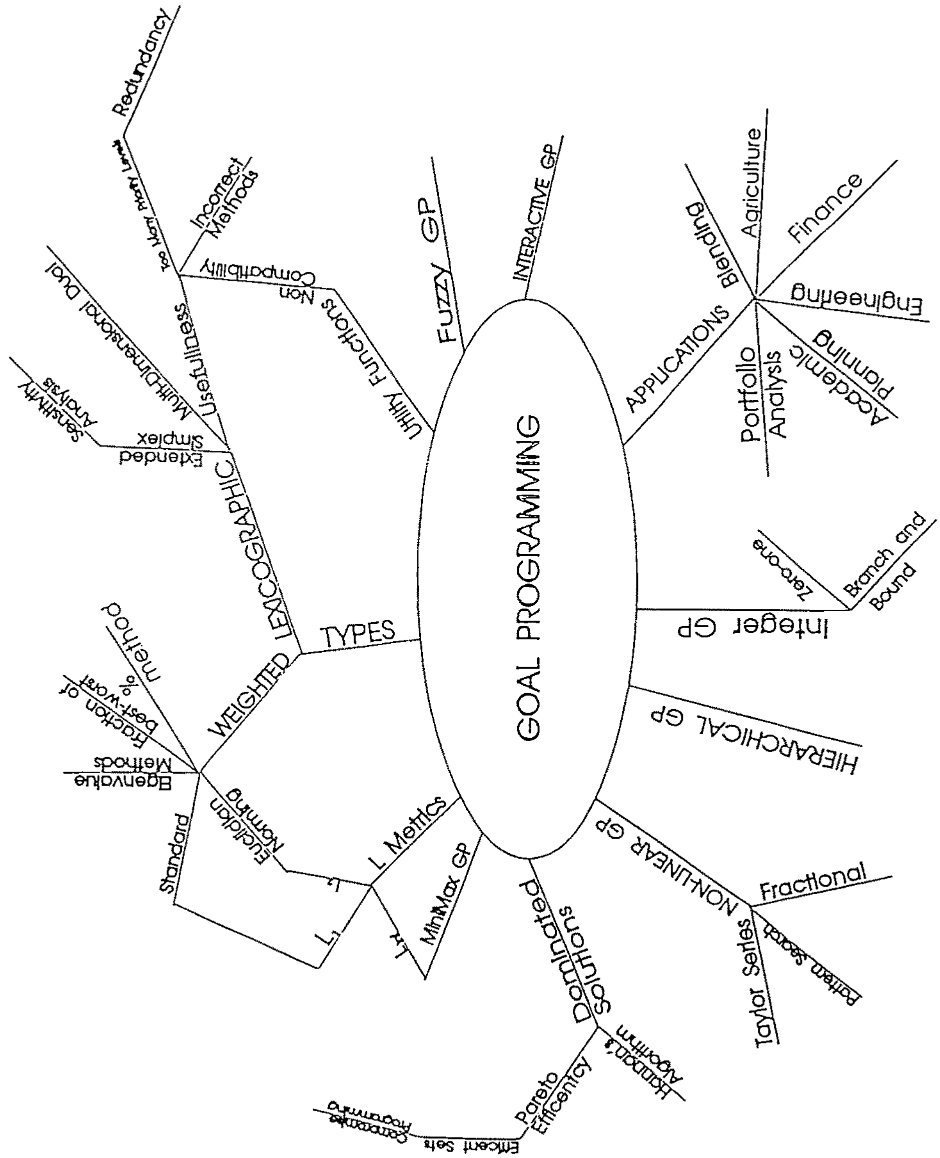

Figure 2. Graphical representation of goal programming topics.

in the dual corresponding to variables in the primal with positive shadow costs at a higher priority level. Ignizio notes that this produces enough speed-up to limit the solution time to (on average) approximately 1.5 times that of a standard simplex solution for the corresponding single-objective model.

Algorithms have also been developed to deal with integer and zero–one lexicographic GP. Lee and Luebbe [47] have developed an algorithm that allows relatively fast solution of smaller scale zero–one GP problems using techniques of constraint aggregation and partitioning as originally developed for standard LGP and integer GP by Arthur and Ravindran [5,3]. Markland and Vickery [50] have developed an integer GP model capable of handling large-scale problems.

2.2. THE MULTI-DIMENSIONAL DUAL

As first shown by Ignizio, a lexicographic GP has a dual similar to that of a linear programme. The main difference is that the right-hand sides of the dual are multi-dimensional and lexicographically ranked. This result obviously follows from the fact that the objective rows in the primal are lexicographically ranked. Hence, the dual can also be solved as a series of sequential linear programmes. A detailed account of work on, and properties of, the multi-dimensional dual can be found in Ignizio's books [29,32].

2.3. APPLICATION AREAS – LEXICOGRAPHIC GP

The majority of papers to date using GP have used the concept of lexicographic GP. A detailed breakdown of GP papers is given in figures 3 and 4. Figure 4 shows that LGP was very popular in the late 1970's and early 1980's. The application areas with an above-average concentration of LGP papers tend to be those where a natural ordering exists, enabling pre-emptive ordering of the priority levels. This subject will be further expanded in section 4. Such areas include academic planning [20], engineering [30] (in this application area, some of the constraints are likely to be nonlinear or fractional, giving rise to special-case nonlinear GP algorithms), health planning [4], inventory management [36], investment planning and portfolio management [46,49], locational analysis [41], marketing [48], quality control [65], transportation models [42], and water resource planning [14]. These references give an example of a use of LGP in the particular subject area. They are not intended to reflect the total work on LGP within that subject area.

3. Weighted GP

Weighted (or non-pre-emptive) GP (WGP) requires no pre-emptive ordering of the objective functions. Instead, all the different deviations are placed in a single priority level objective with different weights to represent their importance.

Algebraically, a WGP has the following structure:

$$\text{minimize} \quad a = \sum_{i=1}^{k} (\alpha_i n_i + \beta_i p_i)$$

$$\text{subject to} \quad f_i(\boldsymbol{x}) + n_i - p_i = b_i, \quad i = 1, \ldots, m, \quad \boldsymbol{x} \in C_s,$$

where C_s is an optional constraint set.

3.1. NORMALISATION TECHNIQUES

One of the major disadvantages of using weighted GP in the past has been the problem of incommensurability (i.e. elements in objective functions being measured in different units). This can cause distorted results if the deviations of each objective are placed into the achievement function without any means of normalisation. For example: A deviation from a cash target of \$1,000,000 can hardly be directly compared with, say, a deviation from an environmental target of 10^{-6} concentration of a substance in the atmosphere! Hence the need for a normalisation procedure. Several normalisation procedures have been suggested by various authors. The most popular are presented below.

(a) *Euclidean normalisation*: First suggested by De Kluyver [19] in 1979, this method divides each objective by the Euclidean (L_2) norm of its coefficients, e.g.

$$3x_1 + 4x_2 + n - p = 16 \rightarrow 3/5x_1 + 4/5x_2 + n^e - p^e = 16/5.$$

As noted by Romero [60], this approach alleviates some of the problems caused by incommensurability but since its critical factor is the coefficients, it can still leave distortions when the values taken by the technical coefficients are small compared with the goal target values.

(b) *Percentage normalisation*: This method is clearly illustrated in Romero [60]. Each objective is first divided through by its right-hand side and then multiplied by 100. The new deviations ($n\%$ and $p\%$) then represent percentage deviations away from the goals, e.g.

$$3x_1 + 4x_2 + n - p = 16 \rightarrow 300/16x_1 + 400/16x_2 + n\% - p\% = 100.$$

The critical factor in this method is the goal target value (b_i). Thus, this method works well except in the case where the target value is very small.

(c) *Scaling between ideal and nadir points*: In this method, we find the minimum (ideal) deviation from the goal for each objective within C_s and label this value g_{ib}. Likewise, the maximum (nadir) deviation from the goal within C_s is also calculated and labelled g_{iw}.

The following scaling function is then applied:

$$[g_{iw} - g_i(n_i, p_i)] / [g_{iw} - g_{ib}].$$

This scales each objective to the interval [0, 1], with 0 representing the minimum possible (ideal) deviation and 1 the maximum possible (nadir) deviation. This method appears both robust and theoretically sound. Problems do occur, however, when the feasible region defined by the constraint set C_s contains some undesirable alternatives, since these alternatives have an effect on the maximal deviation and thus distort the weights for some objectives. Care should therefore be taken on defining C_s if this method is used. A second problem that may occur is the degenerate case in which an objective has a constant deviation over C_s, i.e. $g_{iw} = g_{ib}$. The normalisation process is, however, computationally expensive. For an m objective problem, this method requires an additional $2m$ simplex optimizations to determine the ideal and nadir points for the objectives. An application of this method to an interactive GP framework is given by Masud and Hwang [52].

3.2. APPLICATION AREAS – WEIGHTED GP

As shown in figure 3, weighted GP accounts for about 20% of the applications of GP listed in a recent bibliography by Romero [60]. The breakdown of WGP papers by year in figure 4 further shows WGP applications maintaining their level, whilst LGP applications declined from their peak in the early 1980's. The reason for this is probably due to a better understanding of the theory behind WGP and common consensus being reached on the need for some kind of normalisation procedure to overcome incommensurability problems.

The type of application area in which WGP is likely to be favoured is one in which information about trade-offs between all the objectives is required by the decision maker. This situation will occur where a natural lexicographic structure is not present.

This appears to be the case in planning-type applications. WGP has also been more widely used in commensurable models, which allow direct comparison of objectives.

Application areas with an above-average concentration of WGP papers include accounting and financial planning [2], agricultural planning [21], diet blending [45,57], fishery and forest management [28], manpower planning [23], production planning [58], socio-economic planning [67], and urban/environmental planning [15].

4. Utility functions

A utility function of a single objective has the properties:

$U(g(x)) = 1 \Rightarrow$ decision maker completely saisfied;

$U(g(x)) = 0 \Rightarrow$ decision maker completely dissatisfied.

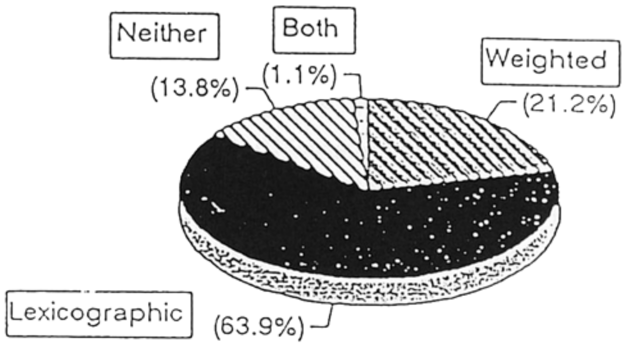

Figure 3. Use of lexicographic and weighted GP in applications.
Source: Romero's bibliography [38].

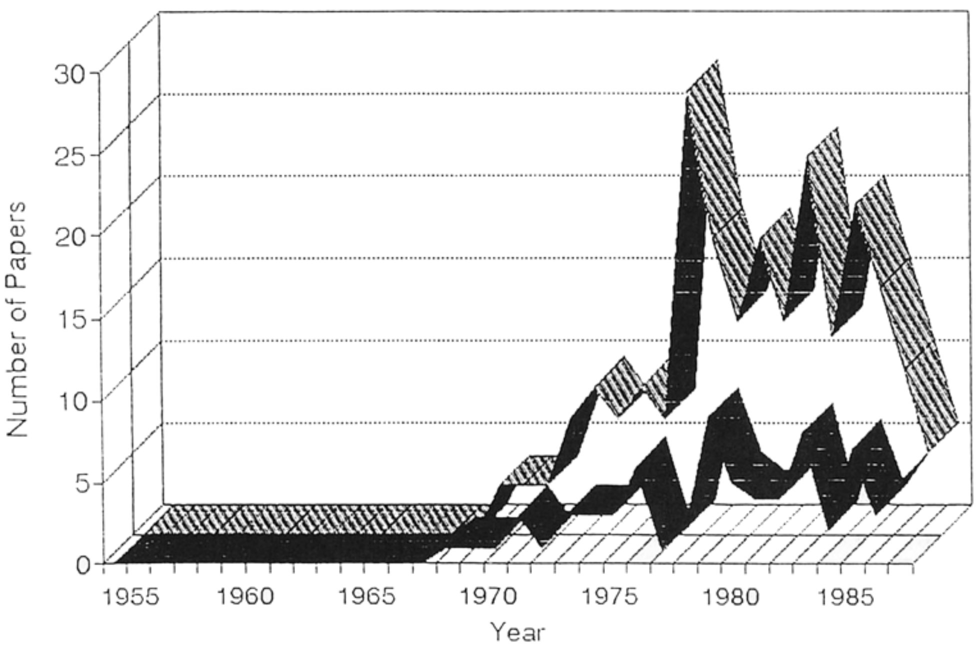

Figure 4. Frequency of lexicographic and weighted GP in application papers 1955–1988.
Source: Romero's bibliography [38].

Hannan [26] identifies three basic types of utility function:

(1) Monotone increasing or decreasing within feasible range. For example, the minimization of cost; this utility function is summed up by the "less is always better" approach.

(2) Monotone increasing followed by monotone decreasing. For example, an order level: too many would imply a holding cost, whilst too few would imply a stockout.

(3) Monotone increasing followed by a constant function ($U(g(x)) = 1$). For example, a diet blending problem: the patient must receive a certain amount of a vitamin but is indifferent to an excess within the feasible range.

The basic GP model limits the representation of the utility function due to the fact that the implied dissatisfaction increases linearly with the deviation away from the goal – the ratio dissatisfaction/deviation being measured by the weight assigned to the deviation in the achievement function.

4.1. UTILITY FUNCTION MODELLING WITH GP

Several approaches have been used to allow a more flexible representation of decision maker dissatisfaction. An overview of these methods is given below.

(1) *Penalty functions*: This method assigns extra goals at points away from the main goal and further penalizes deviations away from these points. This has the effect of increasing the dissatisfaction/deviation ratio beyond these points. Examples of penalty functions: applied to media scheduling problems [18], water planning [8], financial planning [43,44], agriculture [55]. A fuller explanation of penalty function theory can be found in Romero [60].

(2) *Range GP*: This method relaxes the requirement that deviations are measured from a single goal or target and lets the decision maker define a range in which he will be satisfied ($U(g(x)) = 1$). This approach was first introduced by Charnes and Collomb [11] and further developed by Charnes and Cooper during the 1970's [12,13]. Examples of goal interval programming: applied to marine environmental protection [12], and media scheduling [18]. Range GP is most often used in conjunction with the penalty function method described above, and is then defined as goal interval programming [12].

(3) *Adaptation of the Prométhée method*: In a recent paper, Martel and Aouni [51] present a method for greater representation of the decision maker's satisfaction based on the Prométhée method [7]. This method converts the deviations into a [0, 1] utility type function by a series of transformations. It allows for the cases of range and interval GP, as well as allowing discontinuous utility functions, e.g.

$$U(g(x)) = 1 \text{ if } g(x) = b : \text{target met exactly;}$$

$$U(g(x)) = 0 \text{ if } g(x) \neq b : \text{target not met exactly.}$$

This model also allows for the modelling of nonlinear utility functions (e.g. Gaussian). In the latter two cases, however, the resulting model is nonlinear and requires a method of linearization before it can be solved as a standard GP. A simple application to the manufacture of dolls is given in [51].

(4) *Interactive GP*: An interactive GP allows the progressive definition of the decision maker's (DM's) preferences rather than a complete "a priori" definition of the model (and subsequent modelling of the DM's underlying utility function). Hence, these methods alleviate some of the problems incurred in past GP applications due to naive settings of weights, target levels, and naive prioritization in the case of LGP models. See Romero [60] for a general discussion of good and poor modelling practices in GP.

Various interactive methods have been proposed, all of these work on an iterative basis. A kth iteration of an interactive GP algorithm has the general form:

(i) Decision maker presented with information extracted from optimal solution of $(k-1)$th iteration.

(ii) If decision maker satisfied, then stop.
Else decision maker asked to express further his preferences in some way.

(iii) GP model altered in some way to take account of decision maker's preferences.

(iv) GP re-optimized.

The main difference between interactive methods tends to lie in the way information is presented to the decision maker and the different methods used to obtain his preferences (allowing a more accurate representation of his underlying utility function).

Masud and Hwang [52] present an algorithm in which the decision maker is presented with ideal and nadir values for each objective and solutions for a weighted form of (i) all deviations and (ii) the $(m-1)$ permutations of the weighted form containing $m-1$ deviations. The decision maker is then required to alter the models by raising or lowering the level of the goals. A simple application to diet blending is included in [52].

Zionts and Wallenius [71] present a multi-objective programming method in which the decision maker is presented with various trade-offs between the objectives and asked to express satisfaction, indifference, or dissatisfaction at each trade-off. Based on this information, a new set of weights are computed and the algorithm proceeds to the next iteration. This continues until all trade-offs are rejected. This method is successfully modified for goal programming and applied to a diet blending problem by Lara and Romero [45].

Weistroffer [68] presents a nonlinear interactive GP algorithm which iterates on the decision maker altering the target values for the goals. An application to water quality management is included in [68].

4.2. LEXICOGRAPHIC AND WEIGHTED UTILITY FUNCTIONS

The subject of compatibility of LGP and utility function theory has been the cause of controversy in the past. In 1978, Harrald et al. [27] used the results of Debreu [17] to prove:

> For a multiple-objective program with m objectives, having a utility function over the m objectives is theoretically inconsistent with the pre-emptive goal-programming approach of specifying a goal for each of the m objectives and partitioning the goals into different priority classes.

The question then remained: does this result make LGP a theoretically indefensible technique or does there exist a form of lexicographic utility functions for some problems which then require an LGP model? Zeleny [70], a leading figure in the more general field of Multi-Criteria Decision Analysis, argues against lexicographic GP, on the grounds of utility function incompatibility. Ignizio [32] argues in favour of a lexicographic utility function, claiming the utility function of a human life cannot be directly compared with the utility function of cash-savings when building a highway. Romero [60] also defends lexicographic utility functions; he also explains that many of these cases of GP producing incorrect or unexpected results are due to incorrect modelling practices rather than a fundamental flaw in the theory of GP.

On the applications side, LGP was still used extensively throughout the 1980's, as shown in figure 3. Most GP practitioners came to realise that the number of priority levels that exist naturally in a problem is reasonably limited. Ignizio [29] had estimated the likely maximum number of priority levels to be 5. Also the use of utility modelling techniques described in section 4.1 have led to improved LGP models.

The link between weighted GP and utility functions is less controversial. It is widely accepted that a WGP will have a standard underlying utility function. Linear utility functions can be modelled directly. Nonlinear utility functions can be handled using the techniques described in section 4.1. The only condition is that the separate utility functions for each objective must be additive so they can be combined to form an aggregated utility function for the problem.

5. Concluding remarks

This paper has reviewed the major advances in the field of goal programming, including algorithms, applications, normalisation procedures, and utility modelling methods. We hope this paper will inspire continued research in the field of goal programming, and provide useful reference material to practitioners wishing to apply goal programming to practical problem situations.

Works on the pros and cons of goal programming have not been covered in depth. Such papers have been recently summarized in works by Romero [60] and Min and Storbeck [54]. The authors feel that the continued use of GP as an application tool merits further theoretical research on the subject. Some areas of further research identified by this paper are:

(i) Further research into types of normalisation procedures to deal with incommensurability.

(ii) Further reconcilation work between utility function theories and the Goal Programming approach (particularly in the lexicographic case).

The authors will be researching these issues and incorporating the techniques and algorithms discussed in this paper into a single intelligent Goal Programming computer package.

Research in the areas of portfolio GP is also being undertaken, with particular emphasis on developing interactive weighted Goal Programming models.

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