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Diverse Imprecise Goal Programming Model Formulations

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Abstract. The goal programming (GP) model is probably the best known in mathematical programming with multiple objectives. Available in various versions, GP is one of the most powerful multiple objective methods which has been applied in much varied fields. It has also been the target of many criticisms among which are those related to the difficulty of determining precisely the goal values as well as those concerning the decision-maker's near absence in this modelling process. In this paper, we will use the concept of indifference thresholds for modelling the imprecision related to the goal values. Many classical imprecise and fuzzy GP model formulations can be considered as a particular case of the proposed formulation.

Key words: Fuzzy goal programming, goal programming with intervals, indifference thresholds, satisfaction function, decision-maker's preferences.

1. Introduction

The paradigm of multicriterion decision aid processes remains in the fact that the decision-makers consider in their decisions many factors of quite diversified nature and therefore they do not optimize only one single objective. Practically, this is expressed by searching the most satisfying compromise among several objectives which are often conflicting [34]. In fact, the goal programming (GP) model is based on a satisfaction philosophy and may be seen as a human being expression technique, known as intelligent, often marred of ambiguity; this differs considerably from the optimization philosophy generally adopted in mathematical programming [25, 40].

In other terms, the GP model enables the decision-maker to take simultaneously many goals into account in a decision situation where he has to choose the most satisfying action among a set of feasible actions. According to Hwang *et al.* [17], GP comes in the category of the multiple objective programming models with an a priori articulation of the decision-maker's preferences. However, Hannan [16] rather places it between an a priori articulation and no articulation of the decision-maker's preferences since his task is only to determine the goals values. The GP model's popularity is certainly due to the fact that it is simple, easy to understand and easy to apply since it is an extension of the linear mathematical programming for which very performing solution algorithms are available. Charnes and Cooper [7] do not hesitate to qualify this model as very powerful and easy to use.

In the great majority, the variants of the GP model deal with the determined goals for each objective as precise values. So, we assume that the decision-maker determines precisely his aspiration levels. However, Zeleny [40] raises the difficulty of establishing precisely the goal value associated with each objective. In order to model uncertainty and imprecision we can use probability distribution, fuzzy numbers and different types of thresholds [2].

In literature, we find formulation attempts of the GP model in a stochastic environment [8] and a fuzzy environment, namely the works of Narasimhan [26] and Hannan [12, 13]. These two authors are inspired by a membership function notion introduced by Zimmermann [41]. More recently, Inuiguchi and Kume [19] formulated the GP model in a context where goals and technological parameters are expressed with intervals. In this paper we will focus on the case where only the goals associated to the objectives have an imprecise value.

However, these formulations do not take into account, in an explicit way, the decision-maker's preference structure. So, we will present first a brief survey of some works related to the fuzzy goal programming and the GP model with interval. Then, we will use the indifference thresholds concept to characterize the imprecision related to the goal values. The indifference thresholds and some other thresholds are used for modelling the decision-maker's preferences through the satisfaction functions as it is done in Martel and Aouni [22]. We assume that the decision-maker has no information about the exact values of the goals associated to his objectives. For each objective, he indicates only an interval in which the goal value can be situated. Therefore, we assume that the decision-maker will be indifferent towards solutions within this interval. We believe that the model developed in this paper can be considered as more general than several other imprecise goal programming model formulations.

2. The Standard Goal Programming Model

The GP model has been developed in a perspective to respond to the decision-maker's desire to satisfy many objectives at the same time while exploiting the optimization potential in mathematical programming. This model was originally developed by Charnes and Cooper [5] under the following form:

$$\begin{aligned}
\text{Minimize} \quad & Z = \sum_{i=1}^{p} (W_i^+ \delta_i^+ + W_i^- \delta_i^-) \\
\text{Subject to :} \quad & \sum_{j=1}^{n} a_{ij} x_j - \delta_i^+ + \delta_i^- = g_i; \\
& Cx \le c \text{ (system constraints);} \\
& x_j, \delta_i^+ \text{ and } \delta_i^- \ge 0 \quad (\text{for } i = 1, \ldots, p \text{ and } j = 1, 2, \ldots, n).
\end{aligned}$$

Where:

g_i : the goal associated to the objective i;
$x = (x_1, x_2, \ldots, x_n)$: a n-dimensional vector of decision variables;
a_{ij} : technological parameters related to the system constraints;
c : the available resources;
C : matrix of the coefficients related to the system constraints;
W_i^+ : the importance coefficient associated with the positive deviations;
W_i^- : the importance coefficient associated with the negative deviations.

This model has many variants which depend on the context of application. Despite this fact, this model is always the object of many criticisms [16] such as environments of imprecise and stochastic nature, i.e., the goals g_i are not known with certainty. Our interest in this paper is limited to the GP formulation in the context where the goals are imprecise.

3. The Goal Programming Model in an Imprecise Environment

In the standard GP model the goal values are assumed to be deterministic and precise. However, in several application situations the decision-maker is not able to establish exactly the goal value associated with each objective [40]. This imprecision is related to the nature of the decision making context. The goal value can be vague (fuzzy) or it can be expressed by an interval.

3.1. The Fuzzy Goal Programming Model

The first linear programming problem formulation with several objectives by using a fuzzy programming approach was initially proposed by Zimmermann [41]. In his formulation, Zimmermann used the concept of the membership function introduced by Zadeh [39] and Bellman and Zadeh [1]. This concept was used subsequently by other authors to formulate the GP model in an imprecise environment [12, 13, 14, 15, 26, 27, 36].

The fuzzy goal programming (FGP) formulation has been used and adapted to many different fields of application such as: agricultural planning [37], forestry [28], locating banks and capacitated public facilities [23, 24], industry [9, 10, 11, 29, 30, 32], the transportation problem under budgetary constraints [4] and the flight trajectory problem [38]. These applications and the majority of other research in the FGP use the formulations developed in the research works of Narasimhan and Hannan.

Narasimhan [26] and Hannan [12, 13] were the first to give a FGP formulation by using the concept of the membership functions. These functions are defined on the interval [0, 1]. So, the membership function for the *i-th* goal has a value of 1 when this goal is attained and the decision-maker is totally satisfied; otherwise the membership function assumes a value between 0 and 1.

We present here only Hannan's formulation [12] because it is equivalent to the Narasimhan's [26] formulation and it is more simple and efficient since it needs the introduction of less additional constraints and sub-problems to solve.

$$
\begin{array}{ll}
\text{Minimize} & Z = \lambda \\
\text{Subject to :} & \left(\sum_{j=1}^{n} a_{ij} x_j / \Delta_i\right) - \delta_i^+ + \delta_i^- = g_i/\Delta_i; \\
& \lambda + \delta_i^- + \delta_i^+ \leq 1; \\
& Cx \leq c \text{ (system constraints)}; \\
& \lambda, \delta_i^-, \delta_i^+ \text{ and } x_j \geq 0 \text{ (for } j = 1, 2, \ldots, n \text{ and } i = 1, 2, \ldots, p),
\end{array}
$$

where:

Δ_i: the constant of deviation in relation to the aspiration levels g_i. The values of Δ_i are subjectively chosen by the decision-maker.

This formulation incorporates an equivalent linear representation of the following membership function used by Hannan [12]:

$$
\text{membership function} = \begin{cases}
0 \text{ if } \sum_{j=1}^{n} a_{ij} x_j \leq g_i - \Delta_i; \\
\left(\sum_{j=1}^{n} a_{ij} x_j - (g_i - \Delta_i)\right) / \Delta_i \text{ if } g_i - \Delta_i \leq \sum_{j=1}^{n} a_{ij} x_j \leq g_i; \\
\left(g_i + \Delta_i - \sum_{j=1}^{n} a_{ij} x_j\right) / \Delta_i \text{ if } g_i \leq \sum_{j=1}^{n} a_{ij} x_j \leq g_i + \Delta_i; \\
0 \text{ if } \sum_{j=1}^{n} a_{ij} x_j \geq g_i + \Delta_i.
\end{cases}
$$

This function can be represented by the shape below (see Figure 1):

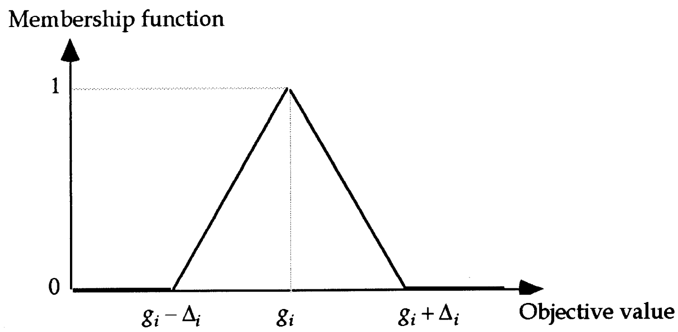

Fig. 1. Linear membership function shape.

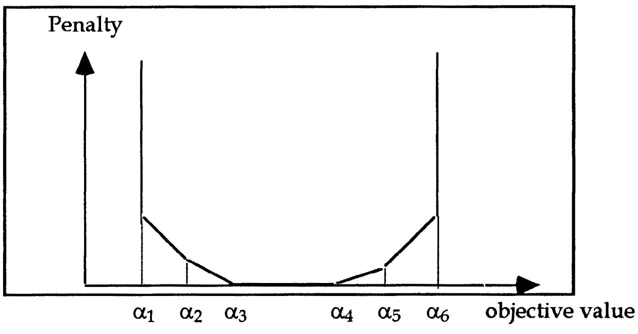

Fig. 2. U-shaped penalty function (five sides)

Ignizio (1982) questions Narasimhan and Hannan's developments concerning the analytical form of the membership functions. Hence, he stresses the fact that the authors have only considered the case where the decision-maker has membership functions of particular forms. In fact, these membership functions are often established without the decision-maker and are, by their nature, very different from his preference functions.

3.2. The Interval Goal Programming Model

In Charnes *et al.* [6] and Charnes and Cooper [7], we find the first GP formulation where goals are expressed with intervals. Deviations in relation to intervals are penalized by linear penalty functions with different slopes. Precisely, these functions change their slope from an interval to another. Therefore, these linear penalty functions are defined on several intervals (see Figure 2).

From Figure 2, there is no penalty inside the target interval $[\alpha_3, \alpha_4]$. The negative deviations ($[\alpha_2, \alpha_3]$ or $[\alpha_1, \alpha_2]$) and the positive deviations ($[\alpha_4, \alpha_5]$ or $[\alpha_5, \alpha_6]$) are penalized according to different marginal penalties. For all the deviations, either positive or negative larger than $\alpha_3 - \alpha_1$ or $\alpha_6 - \alpha_4$, there is an infinite penalty which is equivalent to setting a veto threshold. The decision-maker will not consider the solutions conducting to deviations larger than the veto threshold.

Recently, Jones and Tamiz [20] proposed a penalty goal programming formulation with discontinuous and varying penalty functions levels. Even that the authors consider the goals values as precise and deterministic, their formulation can be used in the situation where these values are defined on an interval.

Also, the concept of penalty functions in the GP model was explored more in the works of Kvanli [21], Romero [33] and Can and Houck [3] who proposed new formulations with imprecise goals. These formulations do not deal in an equal way with the positive and negative deviations compared to the GP standard formulation. This may be considered as an interesting contribution since a positive or a negative interval in relation to any goal does not necessarily have the same effect on the decision-maker. It is important to be able to make the difference at the level of the decision-maker's preferences when a determined goal on a given objective is exceeded or not reached.

In their paper, Inuiguchi and Kume [19] present a GP formulation where the technological parameters and the goals are determined by intervals. These intervals reflect an imprecision associated to the technological parameters and to the goals. The goals g_i are then expressed by an interval having an inferior limit g_i^l and a superior limit g_i^u. This formulation is made up of four mathematical programs. As an illustration, we present one of these programs called, in their paper, "NES-UPP":

$$
\begin{aligned}
\text{Minimize} \quad & Z = \lambda \sum_{i=1}^{p} W_i V_i + (1-\lambda) V^* \\
\text{Subject to:} \quad & \sum_{j=1}^{n} a_{ij}^l x_j + \delta_i^{l-} - \delta_i^{l+} = g_i^l; \\
& \sum_{j=1}^{n} a_{ij}^u x_j + \delta_i^{u-} - \delta_i^{u+} = g_i^u; \\
& \delta_i^{l-} + \delta_i^{l+} \le V_i; \\
& \delta_i^{u-} + \delta_i^{u+} \le V_i; \\
& V_i \le V^*; \\
& Cx \le c \text{ (system constraints);} \\
& \delta_i^{l-}, \delta_i^{l+}, \delta_i^{u-}, \delta_i^{u+} \text{ and } x_j \ge 0 \\
& \quad \text{(for } i = 1, 2, \ldots, p \text{ and } j = 1, 2, \ldots, n\text{);}
\end{aligned}
$$

where:

a_{ij}^l and a_{ij}^u are respectively the lower and upper bounds associated to the technological parameters of the system constraints.

Despite the fact that the decision-maker judges that his goals are imprecise and that he is not in a position to define them exactly, the formulation of Inuiguchi and Kume [19] favours central values of the intervals. Therefore, it is as if the goals associated to various objectives were deterministic and equal to the central value of each interval. Moreover, they proposed a linear penalty function associated to the deviations from the goals (see Figure 3).

As we have seen previously, generally the fuzzy goal programming model as well as the interval goal programming model consider that the membership and penalty functions as linear. Moreover, these functions favour a central value of the deviations from the goal g_i and the shape of the membership or penalty functions is symmetric either inside or outside the target interval.

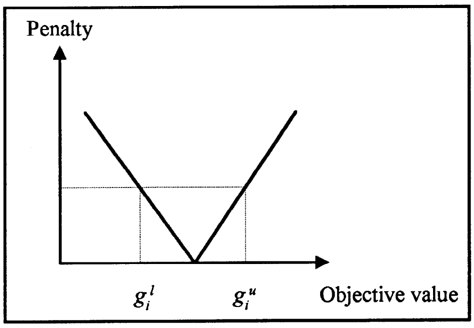

Fig. 3. Penalty function.

4. The Goal Programming With Indifference Thresholds

In a previous paper [22] we proposed a GP model formulation in which the decision-maker's preferences are explicitly introduced. This formulation reads as follows:

$$\begin{aligned}
&\text{Minimize} \quad && Z = \sum_{i=1}^{p} (W_i^+ F_i^+(\delta_i^+) + W_i^- F_i^-(\delta_i^-)) \\
&\text{Subject to :} \quad && \sum_{j=1}^{n} a_{ij} x_j - \delta_i^+ + \delta_i^- = g_i; \\
& && Cx \leq c \text{ (system constraints);} \\
& && \delta_i^-, \delta_i^+ \text{ and } x_j \geq 0 \quad (\text{for } j = 1, 2, \ldots, n \text{ and } i = 1, 2, \ldots, p);
\end{aligned}$$

where:

$F_i(\delta_i)$ is the decision-maker's satisfaction function according to the deviation δ_i. this function may be different from one objective to another whether it is a positive or a negative deviation (see Figure 4(a) and (b)).

This formulation is entirely adapted in situations where goals are imprecise. In fact, if we will consider that the goals ξ_i are fuzzy and defined on the following target interval $[g_i^l, g_i^u]$; that means the ξ_i values can be any point within this interval $[\xi_i \in [g_i^l, g_i^u])$. The decision-maker will be satisfied when the goals deviations are within the interval $[0, \alpha_{i1}]$, where α_{i1} are the indifference thresholds. These thresholds can be fixed as follows:

$$\alpha_{i1}^+ \geq g_i^u - \xi_i;$$

$$\alpha_{i1}^- \geq \xi_i - g_i^l;$$

where:

α_{i1}^+ and α_{i1}^- are the indifference thresholds associated to the positive and negative deviations respectively.

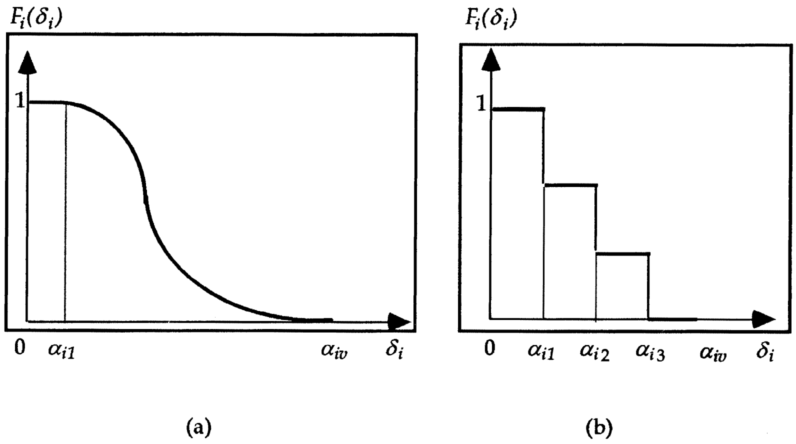

Fig. 4. Satisfaction functions

We assume that the decision-maker has no information about the exact values of his objectives goals and he will be indifferent towards the solutions inside the target interval. So, within the target interval, the satisfaction function is at its maximum level which is 1. Outside this interval, this function is monotonic decreasing and it may take various forms. Moreover, each action with a deviation larger than α_{iv} (α_{iv} is a veto threshold) would be rejected by the decision-maker. In other words, there is an infinite dissatisfaction (infinite penalty) for the deviations which are larger than the veto threshold.

The GP new formulation with imprecise goals values is as follows:

$$
\begin{aligned}
\text{Maximize} \quad & Z = \sum_{i=1}^{p} (W_i^+ F_i^+(\delta_i^+) + W_i^- F_i^-(\delta_i^-)) \\
\text{Subject to :} \quad & \sum_{j=1}^{n} a_{ij}x_j - \delta_i^+ + \delta_i^- = \xi_i; \quad (\text{for } i = 1, 2, \ldots, p) \\
& Cx \leq c; \\
& \delta_i^+ \text{ and } \delta_i^- \leq \alpha_{iv}, \text{ for } i = 1, 2, \ldots, p); \\
& \delta_i^-, \delta_i^+ \text{ and } x_j \geq 0 \quad (\text{for } j = 1, 2, \ldots, n \text{ and } i = 1, 2, \ldots, p).
\end{aligned}
$$

In this formulation the indifference thresholds (α_{i1}) are used to characterize the imprecision associated to the goals values.

5. Discussion About the Diverse Formulations of the Imprecise GP Model

In the FGP and IGP formulations the focus is only on the imprecision related to the goals and there is no explicit modelling of the decision-maker's preferences. In fact, the membership and penalty functions are often established without the

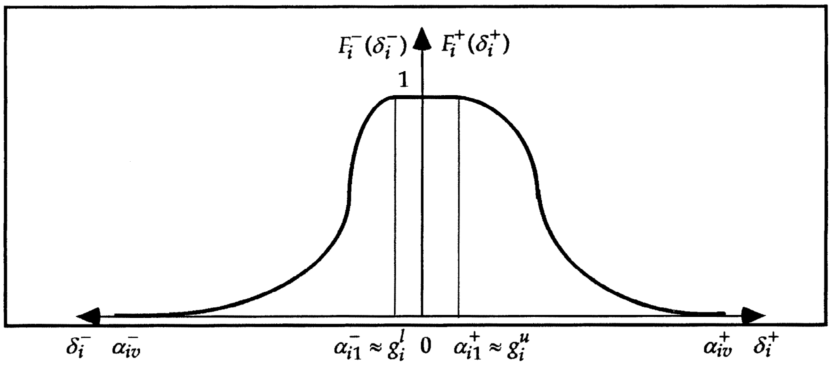

Fig. 5. Satisfaction function .

decision-maker and are usually assumed to be linear on the target interval. These formulations do not add anything to the level of the decision-maker's involvement in the modelling and solution process. In other words, the decision-maker's preference structure has not been introduced in an explicit way in FGP and IGP formulations.

For example, by the resolution of the "max. min." program used in the FGP model, we can obtain some "optimal" solutions which are not equivalent according to a global decision-maker's preferences point of view. If the obtained solutions yield a $\lambda_{\max} = 0.7$, the attainable levels of each objective (which have to be greater than 0.7) can be different from a solution to another. Globally, we usually look for the highest level on each objective.

Moreover, the FGP and the IGP "NES-UPP" formulations favour a central values of the deviations from the goals g_i which are imprecise in nature. So, if we assume that the shape of the membership functions is symmetric, it would mean that the decision-maker has a strict preference for the central values which will be very difficult to justify when he has no idea about the exact values of the goals. Moreover, he can appreciate differently a positive and a negative goal deviations. We believe that the decision-maker should be indifferent towards solutions within the target interval and his satisfaction will decrease outside this interval with different shapes depending on the positive or negative deviations (see Figure 5).

The GP formulation proposed in this paper allows the decision-maker to express explicitly his preferences by different satisfaction levels associated to the goals deviations. The satisfaction functions are not necessarily linear and symmetric as implicitly assumed in the membership and penalty functions used respectively in the FGP (Figure 6) and IGP formulations (Figure 7).

We believe that building up the satisfaction functions is a decision-maker's right, which is very different from the FGP formulation where we use membership functions (in the sense of fuzzy sets). In Inuiguchi and Kume's [19] formula-

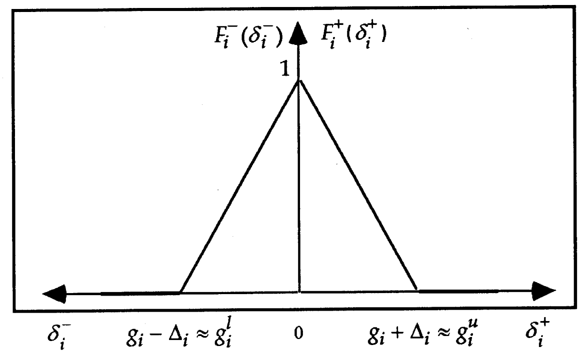

Fig. 6. Satisfaction function equivalent to the FGP linear membership function shape (Figure 1).

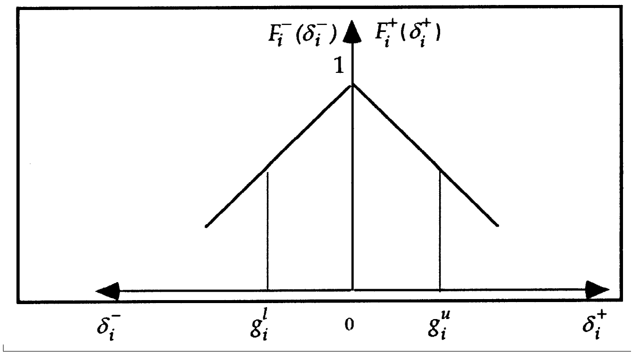

Fig. 7. Satisfaction function equivalent to the IGP "NES-UPP" penalty function shape (Figure 3).

tion, the mathematical model concentrates only on the imprecision without being preoccupied really with the decision-maker's preferences.

Even if the satisfaction functions include partially the relative importance of the different objectives, the decision-maker can introduce explicitly the ponderation of the positive and negative deviations. The relative importance of the objectives is represented in large part by the weighting vector W_i and partially by thresholds values (notably, the veto threshold) in the satisfaction functions $F_i(\delta_i)$. Moreover, by using the thresholds we obtain a partially compensatory model.

6. Conclusion

The imprecise GP model formulation proposed in this paper uses the concept of the indifference thresholds to characterize the imprecision associated to the goals values. This formulation allows the decision-maker to express his satisfaction degrees in relation to the different expectation levels (which are imprecise in nature) of his objectives.

Therefore, this model could be qualified as a decision aid tool since it enables the decision-maker to get more involved in his decision process. Hence, during the problem formulation stage, the decision-maker is required to express his satisfaction degrees in function of observed deviations in relation to the imprecise goals. Moreover, the decision-maker could revise his satisfaction functions in order to make sure that his preference structure is represented in the best way. So, we can qualify our GP formulation as a tool of multicriterion decision aid as Roy conceives it [35].

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