Production Planning using Fuzzy Meta–Goal Programming Model

A. K. Bhargava¹, S. R. Singh² and Divya Bansal³*

¹Department of Mathematics, M.M.H. College, Ghaziabad - 201001, Uttar Pradesh, India. Affiliated: C.C.S. University, Meerut - 250001, Uttar Pradesh, India; dr.bhargavaak@gmail.com
²Department of Mathematics, C.C.S. University, Meerut - 250001, Uttar Pradesh, India; shivrajpundir@gmail.com
³Banasthali University, Rajasthan, India; divyabansal.2008@gmail.com

Abstract

In this paper, fuzzy meta-goal programming model is proposed in a manufacturing plant where the objective is to determine the number of units to be produced and hence sold within the given restrictions. Here, three types of meta-goals are considered which are assumed to have fuzzy bounds to manipulate the degree of attainment for the prioritised goals. Hypothetical production planning problem is used to illustrate the same where, LINDO 11.0 optimizer solver is used to draw results of the problem. The decision-maker is given flexibility by means of meta-goals in expressing their preferences. The production planning problem solved using the proposed model shows that the decision-maker can know establish target values not only for goals but also for relevant achievement functions which are assumed fuzzy in nature thus, providing a new dimension to programming by allowing the decision-maker to establish requirements on different achievement function, rather than limiting his/her opinions to the requirements of a single variant. This approach can be applied to more realistic problems on being more flexible than usual GP, namely, textile, coal, sugar industries, etc.

Keywords: Fuzzy Goal Programming, Fuzzy Meta-Goal Programming Method, Manufacturing Plant, Meta Goals, Production Planning

1. Introduction

After the Second World War, the Industrial world faced a depression to solve the various industrial problems. Industrialist learnt that the techniques of OR can conveniently apply to solve industrial problems. Then onwards, various models of OR/GP have been developed to solve industrial problems. In fact GP models are helpful to the managers to solve various problems; they face in their day to day work. These models are used to minimize the cost of production, increase the productivity and use the available resources carefully and for healthy industrial growth.

Goal programming technique is an efficient method for evaluating international expansion sites and making selection decisions.

In today’s complex organizational environment, the decision maker is regarded as one who attempts to achieve a set of objectives to the fullest possible extent in an environment of conflicting interests, incomplete information and limited resources as studied by Simon¹. To handle multi-objective decision making a unique approach known as Goal Programming (GP) which reflects the Simon’s theory of “satisficing” is widely applied techniques for modern decision-making problems. The advantage of using Goal Programming over other techniques in dealing with real-world decision problems is that it reflects the way managers actually make decisions. Goal Programming allows decision maker to incorporate environmental, organizational and managerial consideration into model through goal levels and priorities. Goal Programming, although far from a panacea, often represents a substantial improvement in the modeling and analysis of the real life situation.

Interest in Goal Programming has increased significantly in the recent past as has its actual implementation. The initial development of the concept of Goal Programming

*Author for correspondence
was due to Charnes and Cooper, in a discussion of which appeared in 1961 although Charnes, Cooper and Ferguson claim that the idea actually originated in 1955. In essence they proposed a model and approach for dealing with certain linear programming problems in which conflict “goals of management” were included as constraints. Since it might well be impossible to satisfy exactly all such goals, one attempts to minimize the sum of the absolute values of the deviation from such goals.

Goal Programming (GP) also known as Multiple-Criteria Decision Making (MCDC) technique is an extension of linear programming problem involving multiple objectives. Each of these objectives is given a goal or target value to be achieved. GP model seeks to minimize the deviations between the desired goals and the actual results to be obtained according to the assigned priorities, that is, certain function of the unwanted deviation variables is minimized.

2. Methodology

Many literatures present different arguments in favor or against the use of the two GP models: Preemptive Goal Programming and Weighted Goal Programming. For example, Gass described the following reasons of how it may be unrealistic for the decision maker to model a multiple objective problem using the preemptive structure. First, it may be very difficult for the decision maker to set absolute goal hierarchy levels because this assumes infinite trade-offs between different levels. Second, the sequential solution technique may cut-off some parts of the solution space, which might be of interest to the decision maker. On the other hand, a decision maker may find determining absolute goal priority levels in some situations more straightforward than determining precise weights for the goals, this might make weighted GP less favourable compared to the preemptive priority GP.

Rad et al. for products of Hafez tile factory during one year suggested an aggregate production planning model with the goals viz. maximizing production capacity of factories, minimizing production cost and also providing the market demands. Silva da proposed multi-choice mixed integer goal programming optimization for real problems in a sugar and ethanol milling company.

Providing crisp definition of goal priorities, in practice, is not an easy task, where multi-objective decision problems are considered. Uncertainty may be inherent in relative importance relations among the goals or alternatively the perception of the relative importance relations among the goals may be vague form the decision maker’s point of view. The decision space and correlation between objectives may also have effects on the definition of importance relations among the goals. Hence, there is a need to develop a FGP model which takes into account these uncertainties and provides a flexible decision making tool. Often, in certain cases the aspiration levels and/or priority factors of the decision-makers and sometimes even the weights to be assigned to the goals are imprecise in nature. In such situations the concepts of fuzzy set theory are useful to achieve desired results.

Bellman and Zadeh set the basic principles of decision making in fuzzy environments, which have been used as building blocks of fuzzy linear programming. Since early 1980s, fuzzy sets have been used in GP models to represent uncertain knowledge about a certain parameter and to represent a satisfaction degree of the decision maker with respect to his/her preference structure. These researchers investigated different types of decision problem using Fuzzy Goal Programming (FGP). Bhargava, Singh and Bansal gave the application of FGP for production planning in industry in order to maximize the production capacity, profit, minimize the extra finishing labor and furnace hours and the manufacturing capacity with different operational constraints, including strategic aim of the company, profit goal, limit on finishing and furnace hours needed, cups manufactured with target values being imprecise in nature; FGP approach to frozen food product distribution of small and medium enterprises considering three major objectives, viz. achieving the total distribution of five products of frozen foods to three different locations, maximizing total profits and minimizing the total manufacturing costs, bakery production to maximize the daily sales profits, minimize overtime and maximize the utility of machines during the daily production of a small and medium enterprise in producing muffins, cupcakes, brownies, cream puff, cheese tarts and egg tarts. Yaghoobi, Jones and Tamiz applied the conventional MINMAX approach to solve FGP problem in GP. While Goal Programming requires the definite aspiration values set by decision maker for each objective that he/she wishes to achieve, in the Fuzzy Goal Programming (FGP) model all these aspiration levels are specified in an imprecise manner. Hannan in 1981 and 1982 assigns aspiration values for the membership functions of the fuzzy goals (which restricts the membership function from full achievement, i.e., unity) and
uses the additive property to aggregate the deviational variables of the membership functions to minimize them. These functions are defined on the interval $[0, 1]$. For example, if the $i$-th goal is attained, then the membership function has the value of 1 and the decision maker is fully satisfied, otherwise the membership function assumes the value between 0 and 1. Throughout this paper a fuzzy goal is considered as a goal with imprecise aspiration level.

Iskander M. G. proposed an exponential membership functions in Fuzzy Goal Programming utilized within two main forms of Fuzzy Goal Program. It showcased the comparison between the lexicographical minimization model and the model with a preemptive goal hierarchy applied to a fuzzy textile production planning problem, where the membership functions of the fuzzy goals are considered exponential with either increasing or decreasing rate of change. It can be concluded that, if the decision-maker is not sure about the tolerance limits of the fuzzy data, it is preferable to use the lexicographical minimization model, in order to minimize the sensitivity of the change in results due to the change in data. Also, the lexicographical minimization model is recommended, when the desirable achievement levels for the goals having top priority level are extremely limited, so as to avoid having infeasible solution when the model with a preemptive goal hierarchy is used. This conclusion is applicable whether in the case of increasing or the case of decreasing rate of change. On the other hand, if the decision-maker is seeking to get different set of results based on different tolerance limits that reflect alternative production scenarios, then the model with a preemptive goal hierarchy can be preferable. Finally, whether in the case of increasing or the case of decreasing rate of change, if an optimal solution exists for each of the two models, the trade-off between not getting zero for any membership function and achieving large values for the membership functions with high priority levels is a main criterion for choosing between the two models.

Taghizadeh et al. suggested optimization of production planning using FGP fulfilling two objectives, reducing the cost of production, increase revenue leading to increased profits using TIVARY simple collective models and collective weighted method. Hajikarimi et al. used the FGP method in order to improve productivity where productivity factors including factors such as data, process, output, business cycles, competitors and government policies are modeled and a systematic model to improve factors in the field of three productivity areas: materials, capital and human resource is provided resulting in better picture of the real systems of production and sales. Ighravwe et al. formulated a bi-objective programming-based facility layout design problem having the objectives to minimise workforce costs and maximise efficiency improvement in a layout. In this procedure, Fuzzy Goal Programming and big-bang big-crunch algorithm is used in order to generate a Pareto solution. The proposed model was tested using a small-scale sachet water production enterprise data.

It is clear that real world practitioners of Goal Programming never accept the first solution of a model as the definitive one. In this sense, some kind of sensitivity analysis is always carried out, taking into account some feedback from the decision-maker. Nevertheless, in many cases this sensitivity analysis is carried out using the same GP variant, while other parameters are changed. The purpose of this paper is to provide the users with a formulation, which allows to explore in a more comfortable way, different possible satisficing solutions using several variants at the same time.

In order to address the above problem it has been suggested to formulate a GP model based upon not in a single variant but in a mix of variants. Another way to address this problem is to use Meta-GP model.

Meta-goal is considered as a simultaneous cognitive evaluation on the degree of achievements for original decision goals considered in a GP model. The meta-goal expressed as the utility function of the model, evaluates undesired deviation of each of the goal function $d_i$ in order to communicate concisely with decision-makers the overall status of decision outcomes.

As different goals contribute differently to the final decision, thus, the sensitivity corresponding to the deviations is represented by appropriate weighting factors. Further, in order to ensure that all goal functions are analyzed on the same scale, normalization is one of the popular technique used as it helps to determine the trade-offs between different decision goals. But the problem here is deviations may not be fixed and thus required to be fuzzy in nature.

3. Developing Model

The purpose of this paper is to develop different possible satisficing solutions using several variants using Fuzzy Meta-Goal Programming model. It has been shown how this approach can be more flexible than the usual GP models allowing to the decision-makers to establish target values not only for the goals but also for another
criterion functions assuming fuzziness. For this three types of Fuzzy Meta-Goals are considered:

**Type 1**: A Fuzzy Meta-Goal relating to percentage sum of unwanted deviations.

**Type 2**: A Fuzzy Meta-Goal relating to the maximum percentage deviation, and

**Type 3**: A Fuzzy Meta-Goal relating to the percentage of unachieved goals.

The Fuzzy Meta-Goal Programming approach can be very helpful for a decision-maker to clarify his/her knowledge of the problem situation and of his/her own preferences.

Let us consider the following general setting:

\[ f_i(x) + n_i - p_i = t_i, \quad i = 1, 2, ..., l \]
\[ g_i(x) \leq b_j, \quad j = 1, 2, ..., m \]

\[ x \in \mathbb{R}^n. \]  \hspace{1cm} (1)

Where \( f_i(x) \) are concave and \( g_i(x) \) are convex functions with \( l \) goals and \( m \) constraints. Further, it is assumed that the unwanted deviation variables are the negative ones. These unwanted deviation variables can be minimized following a lexicographic, weighted or minmax option. The achievement function of the weighted goal programming model is represented as:

\[ \sum_{i=1}^{l} w_i \frac{n_i}{t_i} \]  \hspace{1cm} (2)

Where \( w_i \) represents a preferential weight and the deviation variables have been normalized, by dividing them among their corresponding target values. If the minmax variant is chosen, then the achievement function becomes:

\[ \max \left\{ w_i \frac{n_i}{t_i} \right\} \]

\[ \text{where} \quad 0 \leq \frac{n_i}{t_i} \leq 1. \]  \hspace{1cm} (3)

Representing the minimum maximum percentage weighted deviation from the target values which can be achieved.

Further it is assumed that the decision-maker may want to give aspiration levels for the final values of these achievement functions that is giving goals of the original goals. There are three types of meta-goals can be defined:

**Type 1**: The percentage sum of unwanted deviation variables cannot surpass a certain bound \( Q_1 \), thus, imposing the following constraint:

\[ \sum_{i=1}^{l} w_i \frac{n_i}{t_i} \leq Q_1 \]  \hspace{1cm} (4)

**Type 2**: The maximum percentage deviation variables cannot surpass a certain bound \( Q_2 \), thus, imposing the following set of constraints:

\[ \max \left\{ w_i \frac{n_i}{t_i} \right\} \leq Q_2 \Leftrightarrow \left\{ \frac{n_i}{t_i} - D \leq 0, \quad i = 1, 2, ..., l, \right\} \]
\[ D \leq Q_2, \]  \hspace{1cm} (5)

Where \( D \) represents the maximum percentage weighted deviation.

**Type 3**: The percentage of achieved goals cannot surpass a certain bound \( Q_3 \), thus, imposing the following set of constraints:

\[ \sum_{i=1}^{l} y_i \leq Q_3 \]  \hspace{1cm} (6)

Where \( y_i \) are binary variables and \( M_i \) represent arbitrarily large values that the corresponding attributes cannot achieve with:

\[ \sum_{i=1}^{l} y_i \]

Representing the number of goals that have not been fully achieved.

Further, let us suppose that a type 1 meta-goal is imposed on the set:

\[ L_{u}^{(1)} = C\{1, 2, ..., l\}. \]

Then, the goal takes the form:

\[ \sum_{i=1}^{l} w_i \frac{n_i}{t_i} \leq Q_{u}^{(1)}. \]  \hspace{1cm} (7)

Similarly, for a type 2 meta-goal on the set \( L_{v}^{(2)} \) and type 3 meta-goal on the set \( L_{w}^{(3)} \), we have:

\[ w_i \frac{n_i}{t_i} - D_v \leq 0, \quad i \in L_{v}^{(2)}, \quad D_v \leq Q_{v}^{(2)} \]

and

\[ n_i - M_i y_i, \quad i \in L_{w}^{(3)} \]
\[ \sum_{i=1}^{l} y_i \leq Q_{w}^{(3)} \]
\[ \text{card} \left( L_{w}^{(3)} \right) \]
\[ y_i \in \{0, 1\}, \quad i \in L_{w}^{(3)} \]  \hspace{1cm} (9)

respectively.
The Meta-Goal Programming model as given by Rodriguez-Uria, Caballero, Ruiz and Romero\textsuperscript{34} with r1 type 1 meta-goals, r2 type 2 meta-goals, r3 type 3 meta-goals. In this way, the following meta-GP or [GP]\textsuperscript{2} model is proposed.

\[
\text{Min} \left\{ \beta_1^{(1)}, ..., \beta_1^{(r_1)}, \beta_2^{(1)}, ..., \beta_2^{(r_2)}, \beta_3^{(1)}, ..., \beta_3^{(r_3)} \right\}
\]

Subject to:

\[
f_i(x) + n_i - p_i = t_i, \quad i = 1, 2, ..., l
\]
\[
g_j(x) \leq b_j, \quad j = 1, 2, ..., m
\]
\[
\sum_{i \in L_1} w_i \frac{n_i}{t_i} + a_i^{(1)} - \alpha_i^{(1)} = Q_i^{(1)}, \quad u = 1, 2, ..., r_1
\]
\[
w_i \frac{n_i}{t_i} - D_v \leq 0, \quad i \in L_v^{(2)}, \quad v = 1, 2, ..., r_2
\]
\[
D_v + a_v^{(2)} - \beta_v^{(2)} = Q_v^{(2)}, \quad v = 1, 2, ..., r_2
\]
\[
n_i - M_i y_i, \quad i \in L_v^{(3)}, \quad w = 1, 2, ..., r_3
\]
\[
\sum_{i \in L_v^{(3)}} w_i - a_w^{(3)} - \beta_w^{(3)} = Q_w^{(3)}, \quad w = 1, 2, ..., r_3
\]
\[
y_i \in \{0,1\}, \quad i \in L_v^{(3)}, \quad w = 1, 2, ..., r_3
\]
\[
n_i, p_i \geq 0, \quad i = 1, 2, ..., l
\]
\[
x \in R^n
\]
\[
\alpha_i^{(1)}, \beta_i^{(1)}, \alpha_i^{(2)}, \beta_i^{(2)}, \alpha_i^{(3)}, \beta_i^{(3)} \geq 0.
\]

Using the concept of Fuzzy Goal Programming, let us assume that all the three meta-goals defined above have fuzzy bounds. Here, we define only right-sided (positive deviations penalized) linear function as:

\[
\mu[f_i(x)] = \begin{cases} 
1 & f_i(x) \leq t_i \\
1 - \frac{f_i(x) - t_i}{s_{\text{max}}} & t_i \leq f_i(x) \leq t_i + s_{\text{max}} \\
0 & f_i(x) \geq t_i + s_{\text{max}}
\end{cases}
\]

Where \(\mu[f_i(x)]\) represents the fuzzy membership function with respect to the i-th goal.

Assuming that the Q goals consisting of right-sided membership functions give the following algebraic formulation given by Yaghoobi, Jones and Tamiz\textsuperscript{28}:

\[
\text{Min} Z = \sum_{i=1}^{Q} k_i s_i
\]

Subject to:

\[
f_i(x) - s_i \leq t_i, \quad i = 1, ..., Q
\]
\[
\mu_i + \frac{s_i}{s_{\text{max}}} = 1, \quad i = 1, ..., Q
\]
\[
x \in F
\]
\[
s_i, \mu_i \geq 0, \quad i = 1, ..., Q
\]

Where \(s_{\text{max}}\) represents the positive deviation level beyond the goal at which total dissatisfaction occurs. \(\mu_i\) represents the fuzzy membership function achieved level for the i-th goal.

Thus, the three Fuzzy Meta-Goals are defined as follows:

**FMG1:** \(\sum_{i \in L_1} w_i \frac{n_i}{t_i} \leq Q_i^{(1)}; i \in L_1^{(1)}\)

The membership function for FMG1 is defined as:

\[
\mu \left( \sum_{i \in L_1} w_i \frac{n_i}{t_i} \right) = \begin{cases} 
1 & \sum_{i \in L_1} w_i \frac{n_i}{t_i} \leq Q_i^{(1)} \\beta_i^{(1)} \\
1 - \frac{\sum_{i \in L_1} w_i \frac{n_i}{t_i} - Q_i^{(1)}}{\alpha_i^{(1)}} & Q_i^{(1)} \leq \sum_{i \in L_1} w_i \frac{n_i}{t_i} \leq Q_i^{(1)} + \beta_i^{(1)} \\
0 & \sum_{i \in L_1} w_i \frac{n_i}{t_i} > Q_i^{(1)} + \beta_i^{(1)}
\end{cases}
\]

**Figure 1.** Right-sided linear function.
Production Planning using Fuzzy Meta–Goal Programming Model

FMG2: \[
\text{Max } \sum_{i=1}^{n_1} \frac{w_i n_i}{t_i} \leq Q^{(2)}_v
\]

\[
w_i \frac{n_i}{t_i} - D_v \leq 0, \quad i \in L^{(2)}_v,
\]

\[
D_v \leq Q^{(2)}_v
\]

For FMG2, the membership function is defined as:

\[
\mu[D_v] = \begin{cases} 
1 & ; \quad D_v \leq Q^{(2)}_v \\
1 \frac{D_v - Q^{(2)}_v}{\beta^{(2)}_{v_{\text{max}}}} & ; \quad Q^{(2)}_v \leq D_v \leq Q^{(2)}_v + \beta^{(2)}_{v_{\text{max}}} \\
0 & ; \quad D_v \geq Q^{(2)}_v + \beta^{(2)}_{v_{\text{max}}}
\end{cases}
\]

FMG3: \[
 n_i - M_i y_i \leq 0, \quad i \in L^{(3)}_w
\]

\[
\sum_{i \in L^{(3)}_w} y_i \leq Q^{(1)}_w
\]

\[
y_i \in \{0,1\}, \quad i \in L^{(3)}_w
\]

Again for FMG3, the membership function is defined as:

\[
\mu \left( \sum_{i \in L^{(3)}_w} y_i \right) = \begin{cases} 
1 & \sum_{i \in L^{(3)}_w} y_i \leq Q^{(1)}_w \\
1 \frac{\sum_{i \in L^{(3)}_w} y_i - Q^{(1)}_w}{\beta^{(1)}_{w_{\text{max}}}} & \sum_{i \in L^{(3)}_w} y_i \leq Q^{(1)}_w + \beta^{(1)}_{w_{\text{max}}} \\
0 & \sum_{i \in L^{(3)}_w} y_i \geq Q^{(1)}_w + \beta^{(1)}_{w_{\text{max}}}
\end{cases}
\]

Thus, FMGP with \( r_1 \) type 1 meta-goals, \( r_2 \) type 2 meta-goals and \( r_3 \) type 3 meta-goals is formulated as:

\[
\text{Min } \left\{ \sum_{u=1}^{r_1} \beta_{u_{\text{max}}}^{(1)}, \sum_{v=1}^{r_2} \beta_{v_{\text{max}}}^{(2)}, \sum_{w=1}^{r_3} \beta_{w_{\text{max}}}^{(3)} \right\}
\]

Subject to:

\[
f_i(x) + n_i - p_i = t_i, \quad i = 1,2,\ldots,l
\]

\[
g_j(x) \leq b_j, \quad j = 1,2,\ldots,m
\]

\[
\sum_{i \in L^{(1)}_u} w_i \frac{n_i}{t_i} - \beta_{u}^{(1)} \leq Q_{u}^{(1)}, \quad u = 1,2,\ldots,r_1
\]

\[
\mu \left( \sum_{i \in L^{(1)}_u} w_i \frac{n_i}{t_i} + \beta_{u}^{(1)} \right) = 1, \quad u = 1,2,\ldots,r_1
\]

\[
w_i \frac{n_i}{t_i} - D_v \leq 0, \quad i \in L^{(2)}_v,
\]

\[
D_v - \beta^{(2)}_v \leq Q^{(2)}_v, \quad v = 1,2,\ldots,r_2
\]

\[
\mu(D_v) + \frac{\beta^{(2)}_v}{\beta^{(2)}_{v_{\text{max}}}} = 1, \quad v = 1,2,\ldots,r_2
\]

\[
n_i - M_i y_i \leq 0, \quad i \in L^{(3)}_w,
\]

\[
\sum_{i \in L^{(3)}_w} y_i \leq Q^{(1)}_w
\]

\[
y_i \in \{0,1\}, \quad i \in L^{(3)}_w
\]

\[
x \in \mathbb{R}^n
\]

\[
\beta_{u}^{(1)}, \beta_{v}^{(2)}, \beta_{w}^{(3)} \geq 0.
\]

4. An Illustrative Example

To illustrate the functioning of the Fuzzy Meta-Goal Programming approach, let us consider the following set of goals and constraints for a production planning problem, where variables \( x_i \) and \( p_i \) represents the number of unit of product A and B manufactured, respectively.

4.1 Goals

\[
6250 x_1 + 5000 x_2 + n_1 - p_1 = 200000; \quad \text{(Profit level)}
\]

\[
1375 x_1 + 1025 x_2 + n_2 - p_2 = 36000; \quad \text{(Working capital available)}
\]

\[
120 x_1 + 180 x_2 + n_3 - p_3 = 4000; \quad \text{(Annual labour hours available)}
\]

\[
400 x_1 + n_4 - p_4 = 2000; \quad \text{(Annual labour hours available to manufacture product A)}
\]

\[
450 x_1 + n_5 - p_5 = 2000; \quad \text{(Annual labour hours available to manufacture product B)}
\]

\[
35 x_1 + 35 x_2 + n_6 - p_6 = 1000; \quad \text{(Machine hours available)}
\]

\[
x_1 + x_2 + n_7 - p_7 = 15; \quad \text{(Minimum number of units of A and B together to be manufactured)}
\]
4.2 Constraints

6250 \( x_1 + 5000 x_2 \geq 75000 \); (Profit-break-even point)

The normalizing factor will be the respective target value for each goal. The unwanted deviation variables for this example are as follows:

\[ n_1, p_1, p_2, p_3, p_4, p_5, n_6, p_6, n_7, p_7 \]

Thus, weighted goal programming problem is defined as:


Subject to:

\[ 6250 x_1 + 5000 x_2 + n_1 - p_1 = 200000; \]
\[ 1375 x_1 + 1025 x_2 + n_2 - p_2 = 36000; \]
\[ 120 x_1 + 180 x_2 + n_3 - p_3 = 4000; \]
\[ 400 x_1 + n_4 - p_4 = 2000; \]
\[ 450 x_1 + n_5 - p_5 = 2000; \]
\[ 35 x_1 + 35 x_2 + n_6 - p_6 = 1000; \]
\[ x_1 + x_2 + n_7 - p_7 = 15; \]
\[ 6250 x_1 + 5000 x_2 \geq 75000; \]
\[ x_i, n_i, p_i \geq 0 \quad (i = 1, 2, 3, 4, 5; j = 1, 2, \ldots, 11) \]

Using the goal programming methodology, the solution is:

\[ x_1 = 8.44, x_2 = 4.44; \]
\[ n_1 = 125000, p_1 = 0, n_2 = 19833.3, p_2 = 0, n_3 = 2186.67, p_3 = 0, n_7 = 0, \]
\[ p_4 = 1377.78, n_5 = 0, p_5 = 0, n_6 = 548.89, p_6 = 0, n_7 = 21.1, \]
\[ p_7 = 0. \]

Objective function (Total deviation): 2.003

Let us assume that the decision-maker does not consider acceptable the above solution. Thus, the above weighted goal programme is extended to a Meta-Goal Programme with the following three meta-goals:

MG1: The percentage maximum deviation from all goals should be less than or equal to 2.10.

MG2: The maximum percentage deviation from any goal should be less than or equal to 0.60.

MG3: Number of goals unsatisfied should be less than or equal to 4.

Thus, the meta-GP formulation is given as:

Min: \( (\beta_1) + (\beta_2) + (\beta_3) \)

Subject to:

\[ 6250 x_1 + 5000 x_2 + n_1 - p_1 = 200000; \]
\[ 1375 x_1 + 1025 x_2 + n_2 - p_2 = 36000; \]
\[ 120 x_1 + 180 x_2 + n_3 - p_3 = 4000; \]
\[ 400 x_1 + n_4 - p_4 = 2000; \]
\[ 450 x_1 + n_5 - p_5 = 2000; \]
\[ 35 x_1 + 35 x_2 + n_6 - p_6 = 1000; \]
\[ x_1 + x_2 + n_7 - p_7 = 15; \]
\[ 6250 x_1 + 5000 x_2 \geq 75000; \]
\[ n_1 - 20000 D = 0; \]
\[ p_2 - 36000 D = 0; \]
\[ p_3 - 4000 D = 0; \]
\[ p_4 - 2000 D = 0; \]
\[ p_5 - 20000 D = 0; \]
\[ (n_6 + p_6) - 10000 D = 0; \]
\[ n_7 - 15 D = 0; \]
\[ n_1 - 2000000 y_i = 0; \]
\[ p_2 - 3600000 y_2 = 0; \]
\[ p_3 - 400000 y_3 = 0; \]
\[ p_4 - 200000 y_4 = 0; \]
\[ p_5 - 200000 y_5 = 0; \]
\[ (n_6 + p_6) - 10000 y_6 = 0; \]
\[ n_7 - 150 y_7 = 0; \]
\[ n_1/200000 + p_1/36000 + p_2/4000 + p_4/2000 + p_5/2000 + (n_6 + p_6)/1000 + n_7/15 + \alpha_i - \beta_i = 2.10 \]
\[ D + \alpha_i - \beta_2 = 0.60 \]
\[ (y_1 + y_2 + y_4 + y_5 + y_6 + y_7)/7 + \alpha_i - \beta_3 = 4/7 \]
\[ x_i, n_i, p_j \geq 0 \quad (i = 1, 2, 3, 4, 5; j = 1, 2, \ldots, 11) \]
\[ y_i \in \{0,1\} \]

Where, \( y_i = \begin{cases} 1, & \text{if goal } i \text{ is not satisfied} \\ 0, & \text{otherwise} \end{cases}, i = 1, 2, \ldots, 11. \)

The solution for the above meta-goal programming problem is the following:

\[ x_1 = 8.44, x_2 = 4.44; \]
\[ n_1 = 125000, p_1 = 0, n_2 = 19833.3, p_2 = 0, n_3 = 2186.67, p_3 = 0, \]
\[ p_4 = 1377.78, n_5 = 0, p_5 = 0, n_6 = 548.89, p_6 = 0, n_7 = 21.1, \]
\[ p_7 = 0. \]

Now, let us assume that that the target values of the meta-goals is assumed to be fuzzy in nature and thus define the three meta-goals as follows:

FMG1: The percentage maximum deviation from all goals should lie within the range of 1.80 to 2.10.
FMG2: The maximum percentage deviation from any goal should lie within the range of 0.58 to 1.25

FMG3: Number of goals unsatisfied should lie within the range of 3 to 5.

Thus, the membership functions are defined as:

\[ \mu_{yi} \begin{cases} \frac{(\beta_{yi})/0.3}{(\beta_{yi})/0.67 + (\beta_{yi})/3} & \text{if goal } i \text{ is not satisfied} \\ 1 & \text{otherwise} \end{cases} \]

The solution for the above Fuzzy Meta-Goal Programming problem is the following:

\[
\begin{align*}
\beta_1 &= 0.2035, \quad \beta_2 = 0.1089, \quad \beta_3 = 0.143; \\
\mu_1 &= 0.32, \quad \mu_2 = 0.84, \quad \mu_3 = 0.93.
\end{align*}
\]

5. Conclusion

The above solution is close to weighted goal programming and Meta-Goal Programming problem. From the above solution one can conclude that only three goals namely goals 2, 3, 5 are fully satisfied. The FMGs 2 and 3 are much more achieved with the maximum percentage deviation from any goal to be 0.689 lying within the range 0.58 to 1.25 and number of unsatisfied goals to be 4 lying within the range 3 to 5.

From this paper the decision-maker can now establish target values not only for the goals but also for relevant achievement functions which are assumed fuzzy in nature. Thus, Fuzzy Meta-Goal Programming model can be seen as providing a new dimension to programming by allowing the decision-maker to establish requirements on different achievement functions, rather than limiting his/her opinions to the requirements of a single variant. Thus, this approach is considered as a third stage to the second stage of Meta-Goal Programming after the traditional goal programming problem has been solved.

This approach is much more flexible than usual GP formulations and can be applied to more realistic problems with non-linear goals and/or non-continuous variables.

6. References


