A Fuzzy Goal Programming Model for Bakery Production

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Abstract-This paper addresses the production planning problem with different operational constraints, including the budget of the company, labor, limit on hours needed. The fuzzy goal programming technique is used 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. As in real world problems 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, where the weights are determined using Analytical Hierarchy Process. Further, LINDO 11.0 optimizer solver is used to draw results of the problem.

Key words-Bakery; fuzzy goal programming; production planning; small and medium enterprise; analytical hierarchy process.

1. INTRODUCTION

Production planning involves multiple objectives such as to maximize profit or minimize cost and is formulated to a single-objective function in linear programming. But, many researchers and practitioners are increasingly aware of presence of multiple objectives in real-life problems [1, 33]. In solving the real life situations with multiple objectives, the decision makers (DM) used goal programming (GP) technique to determine optimal production plans. It is regarded as the most widely used multi-criteria decision making technique [29].

For an efficient production planning system it is necessary to grasp the environment in terms of customers, products and production process [21]. Goal programming extends linear programming to problems which involve multiple objectives. Here, instead of maximizing or minimizing the objective function, the deviation between the desired goals is minimized according to the assigned priorities [1]. It is necessary to specify aspiration levels for the objectives and aims to reduce the deviations from aspiration levels. In the case of a problem with nonequivalent goals the weight or priority of the goal is reflected through its deviation variables. Often, in real world problems the aspiration levels and/or priority factors of the DM, and sometimes even the weights to be assigned to the goals, are imprecise in nature. In such situations the use of fuzzy set theory [34] comes in handy. Goal programming popularity is increasing day by day as it is useful in decision making policies which aims at optimizing resources available such as food product distribution of small and medium enterprises [13], recreational Tourism activities [8], utility function for fund allocation of a university library [6],...
scheduling political campaign visits [12], nutrient management for chilli plantation [10], nutrient management for pineapple cultivation [11], and stock market portfolio [9].

The use of fuzzy set theory in GP was first considered by Narasimhan [18], Hannan [3, 4, 5], Narasimhan [19], Ignizio [15]. Rubin and Narsimhan [23] and Tiwari et al. [31, 32] have investigated various aspects of decision problem using FGP. An extensive review of these papers is given by Tiwari et al. in 1985.

The main difference between fuzzy goal programming (FGP) and GP is that the GP requires the definite aspiration values set by DM for each objective that he/she wishes to achieve, whereas in FGP all these aspiration levels are specified in an imprecise manner. Hannan [4] 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. Throughout this paper a fuzzy goal is considered as a goal with imprecise aspiration level.

In conventional GP the simple additive model for m goals \( G_i(x) \) with deviational variables \( p_i, n_i \) is defined as:

\[
\text{Minimize } \sum_{i=1}^{m} (p_i + n_i)
\]

Subject to
\[
G_i(x) + n_i - p_i = g_i, \quad (1)
\]
\[
p_i \cdot n_i = 0,
\]
\[
p_i, n_i, x \geq 0, \quad i = 1, 2, ..., m,
\]

where \( g_i \) represents the aspiration level of the \( i-th \) goal. Here we use a similar model using membership function instead of deviational variables.

### II. METHODOLOGY

The proposed approach is based on the fuzzy goal programming (FGP). The FGP technique is applied in which AHP is applied to determine the preferential weights of the goal. The objective of carrying out this study is to develop a FGP model to a real life production situation for a small and medium Enterprise (SME), Jemy’s Bakery, producing bakery products in the town of Pekan, Pahang. Due to the high demand of products and the selling price of bakery products being relatively affordable, Jemy's Bakery needs to optimize its production planning in order to compete with other bakeries in its vicinity. The optimization goals are maximizing its daily sales profit, minimizing overtime and maximizing the utility of machines used in the production of muffins and cupcakes, brownies, cream puff, cheese tarts and egg tarts. This example is taken for case study from Hassan et al. [7].

#### A. Fuzzy Goal Programming Model:

Now, further consider the FGP problem formulated as:

Find \( X \)

To satisfy

\[
G_i(X) \% g_i, \quad i = 1, 2, ..., m,
\]

Subject to

\[
AX \leq b,
\]
\[
X \geq 0,
\]

where \( X \) is an \( n \)-vector with components \( x_1, x_2, ..., x_n \) and \( AX \leq b \) are system constraints in vector notation. The symbol ‘\( \% \)' refers to the fuzzification of the aspiration level (i.e., approximately greater than or equal to). The \( i-th \) fuzzy goal \( G_i(X) \% g_i \) in (2) signifies that the DM is satisfied even if less than the \( g_i \) up to certain tolerance limit is
attained. A linear membership function $\mu_i$ for the $i$-th fuzzy goal $G_i(x)$ can be expressed according to Zimmermann [1976, 1978] as:

$$
\mu_i = \begin{cases} 
1 & \text{if } G_i(x) \geq g_i, \\
\frac{G_i(x) - L_i}{g_i - L_i} & \text{if } L_i \leq G_i(x) \leq g_i, \\
0 & \text{if } G_i(x) \leq L_i
\end{cases}
$$

(3)

where $L_i$ is the lower tolerance limit for the fuzzy goal $G_i(x)$. In case of the goal $\hat{G}_i(x) - g_i$, the membership function is defined as:

$$
\mu_i = \begin{cases} 
1 & \text{if } G_i(x) \leq g_i, \\
\frac{U_i - G_i(x)}{U_i - g_i} & \text{if } g_i \leq G_i(x) \leq U_i, \\
0 & \text{if } G_i(x) \geq U_i
\end{cases}
$$

(4)

where $U_i$ is the upper tolerance limit.

The additive model of the FGP problem (2) is formulated by adding the membership functions together as:

$$
\text{Maximize } V(\mu) = \sum_{i=1}^{m} \mu_i
$$

(5)

Subject to

$$
AX \leq b, \\
\mu_i \leq 1, \\
X, \mu_i \geq 0, i = 1, 2, ..., m,
$$

where $V(\mu)$ is called the fuzzy achievement function or fuzzy decision function.

### B. Fuzzy Goal Programming Problem:

The summary of data set used in this study is given in Table 2, Table 3, Table 4 and Table 5.

#### Table 2: The Cost, Price and Profit for Each Product

<table>
<thead>
<tr>
<th>Products</th>
<th>Costs (RM)</th>
<th>Prices (RM)</th>
<th>Profits (RM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Muffin</td>
<td>0.24</td>
<td>1.00</td>
<td>0.76</td>
</tr>
<tr>
<td>Cupcake</td>
<td>0.38</td>
<td>2.00</td>
<td>1.62</td>
</tr>
<tr>
<td>Brownie</td>
<td>0.42</td>
<td>1.50</td>
<td>1.08</td>
</tr>
<tr>
<td>Cream Puff</td>
<td>0.14</td>
<td>1.00</td>
<td>0.86</td>
</tr>
<tr>
<td>Cheese Tart</td>
<td>0.26</td>
<td>1.20</td>
<td>0.94</td>
</tr>
<tr>
<td>Egg Tart</td>
<td>0.19</td>
<td>1.00</td>
<td>0.81</td>
</tr>
</tbody>
</table>

#### Table 3: Major Ingredients for Each Product for One Unit in Grams

<table>
<thead>
<tr>
<th>Ingredients for Each Product</th>
<th>Muffin</th>
<th>Cupcake</th>
<th>Brownie</th>
<th>Cream Puff</th>
<th>Cheese Tart</th>
<th>Egg Tart</th>
</tr>
</thead>
<tbody>
<tr>
<td>Margarine</td>
<td>8.425</td>
<td>5.000</td>
<td>1.714</td>
<td>4.833</td>
<td>4.857</td>
<td>4.857</td>
</tr>
<tr>
<td>Sugar</td>
<td>11.250</td>
<td>9.370</td>
<td>7.143</td>
<td>2.667</td>
<td>2.143</td>
<td>2.571</td>
</tr>
<tr>
<td>Egg</td>
<td>9.000</td>
<td>10.000</td>
<td>3.428</td>
<td>8.000</td>
<td>2.428</td>
<td>5.000</td>
</tr>
</tbody>
</table>
Let the tolerance limit of the above 3 goals be (560, 500, 465). Then the above problem as FGP is defined as:

Maximize \( \sum_{i=1}^{3} \mu_i \) with equal weights of all the three goals

Subject to

\[ \mu_1 = (0.76 x_1 + 1.62 x_2 + 1.08 x_3 + 0.86 x_4 + 0.94 x_5 + 0.81 x_6 - 560)/(600 - 560) \]

\[ \mu_2 = [500 - (0.25 x_1 + 1.5 x_2 + 1 x_3 + 1 x_4 + 0.75 x_5 + 0.75 x_6)]/(500 - 480) \]

\[ \mu_3 = (1.5 x_1 + 1.25 x_2 + 1 x_3 + 0.5 x_4 + 0.5 x_5 + 0.5 x_6 - 465)/(480 - 465) \]

\[ \mu_i \leq 1 \ (i = 1, 2, 3) \]

Hard constraints

\[ 9.125 x_1 + 8.33 x_2 + 2.857 x_3 + 4.167 x_4 + 8.285 x_5 + 8.285 x_6 \leq 4500 \]

\[ 8.425 x_1 + 5.0 x_2 + 1.714 x_3 + 4.833 x_4 + 4.857 x_5 + 4.857 x_6 \leq 3500 \]

\[ 11.25 x_1 + 9.37 x_2 + 7.143 x_3 + 2.667 x_4 + 2.143 x_5 + 2.571 x_6 \leq 3500 \]

\[ 9 x_1 + 10 x_2 + 3.428 x_3 + 8 x_4 + 2.428 x_5 + 5 x_6 \leq 4000 \]

\[ 11 x_2 + 6.667 x_3 \leq 1500 \]

\[ 4.167 x_4 + 5.714 x_6 \leq 1000 \]

\[ 3.571 x_5 \leq 400 \]

\[ x_1, x_2, x_3, x_4, x_5, x_6, n_1, p_1, n_2, p_2, n_3, p_3 \geq 0 \]

\[ \mu_i \geq 0 \ (i = 1, 2, 3). \]

where,

\[ x_1 = \text{Number of muffins produced per day} \]
\[ x_2 = \text{Number of cupcakes produced per day} \]
\[ x_3 = \text{Number of brownies produced per day} \]
\[ x_4 = \text{Number of cream puff produced per day} \]
\[ x_5 = \text{Number of cheese tarts produced per day} \]
\[ x_6 = \text{Number of egg tarts produced per day} \]
\[ p_1 = \text{Overachievement of profit target} \]
\[ n_1 = \text{Underachievement of profit target} \]
\[ p_2 = \text{Overtime of the labor working hours (overutilization)} \]
\[ n_2 = \text{Idle time of the labor working hours (underutilization)} \]
\[ p_3 = \text{Overutilization of machine usage} \]
\[ n_3 = \text{Underutilization of machine usage} \]

III. RESULTS AND DISCUSSION

Solving the above problem by LINDO 11.0, we obtain the following results:
\[ x_1 = 103.8732, x_2 = 136.3636, x_3 = 0, \]
\[ x_4 = 75.531, x_5 = 112, x_6 = 119.93, \]
\[ \mu_1 = 0.18, \mu_2 = 1, \mu_3 = 1 \]

The achievement level of the three goals is:
\[ G(1) = 567.24, G(2) = 480, G(3) = 480. \]

It may be noted that the FGP problem (which corresponds to equal importance of goals), \(G(2)\) and \(G(3)\) (\(\mu_2\) and \(\mu_3\)) have achieved fully whereas the first goal \(G(1)\) with \(\mu_1\) are achieved partially.

C. Weighted Fuzzy Goal Programming Model:

If in a FGP model it is required to show the relative importance of the goals/objectives, then weighted additive model is widely used which is shown below:

Maximize \[ V(\mu) = \sum_{i=1}^{m} w_i \mu_i \] (8)

Subject to
\[ \mu_i = \frac{G_i(X) - L_i}{g_i - L_i}, \]
\[ AX \leq b, \]
\[ \mu_i \leq 1, \]
\[ X, \mu_i \geq 0, i = 1, 2, ..., m, \]

where \(w_i\) is the relative weight of the \(i\)-th fuzzy goal.

The DM’s task to assess the relative importance of the goals is the major difficulty of this method. However, there are some good approaches in the literature to assess these weights. We may mention in this regard the eigenvector method of Saaty [28], a geometric averaging procedure for constructing supertransitive approximations to binary comparison matrices by Narasimhan [20], the entropy method of Jaynes [16]. Ozdamar et al. [22] introduced hierarchical decision support for production planning using case study.

Here, the relative weights are determined using Analytic Hierarchy Process - A multicriteria decision making approach in which factors are arranged in a hierarchical structure. Two purposes are solved by arranging the goals, attributes, issues, and stakeholders in a hierarchy. First, it provides an overall view of the complex relationships inherent in the situation; and second it helps the decision maker assess whether the issues in each level are of the same order of magnitude, so he can compare such homogeneous elements accurately. A basic contribution to the subject of this paper, the Analytic Hierarchy Process (AHP) is how to derive relative scales using judgment or data from a standard scale, and how to perform the subsequent arithmetic operation on such scales avoiding useless number crunching. The judgments are given in the form of paired
comparisons [24, 25, 26, 27]. One of the uses of a hierarchy is that it allows us to focus judgment separately on each of several properties essential for making a sound decision. The most effective way to concentrate judgment is to take a pair of elements and compare them on a single property without concern for other properties or other elements. This is why paired comparisons in combination with the hierarchical structure are so useful in deriving measurement.

Prof. Saaty proved that for consistent reciprocal matrix, the largest Eigen value is equal to the number of comparisons, or \( \lambda_{\text{max}} = n \). Then he gave a measure of consistency, called Consistency Index (CI) as deviation or degree of consistency using the following formula:

\[
CI = \frac{\lambda_{\text{max}} - n}{n - 1}
\]

Knowing the Consistency Index, the next question is how do we use this index? Again, Prof. Saaty proposed that we use this index by comparing it with the appropriate one. The appropriate Consistency Index is called Random Consistency Index (RI).

He randomly generated reciprocal matrix using scale \( \frac{1}{9}, \frac{1}{8}, \ldots, 1, \ldots, 8, 9 \) (similar to the idea of Bootstrap) and get the RI to see if it is about 10% or less. The average random consistency index of sample size 500 matrices is shown in the table below:

<table>
<thead>
<tr>
<th>N</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>RI</td>
<td>0.0</td>
<td>0.0</td>
<td>0.58</td>
<td>0.9</td>
<td>1.12</td>
<td>1.24</td>
<td>1.32</td>
<td>1.41</td>
<td>1.45</td>
<td>1.49</td>
</tr>
</tbody>
</table>

Then, he proposed what is called Consistency Ratio (CR), which is a comparison between Consistency Index and Random Consistency Index, or in formula:

\[
CR = \frac{CI}{RI}
\]

If the value of Consistency Ratio is smaller or equal to 10%, the inconsistency is acceptable. If the Consistency Ratio is greater than 10%, we need to revise the subjective judgment.

Weighted Fuzzy Goal Programming Problem:

Now let us apply AHP approach to find the preferential weights of the three goals with their priorities by first developing the pairwise comparison matrix

\[
M = \begin{bmatrix}
1 & 3 & 5 \\
1/3 & 1 & 4 \\
1/5 & 1/4 & 1 \\
\end{bmatrix}
\]

Applying the above approach proposed by Prof. Saaty[28], the preferential weights attached to the three goals is specified as:

\[
\begin{bmatrix}
0.645888 \\
0.252239 \\
0.101874 \\
\end{bmatrix}
\]

These are the weights to be attached to each goal respectively.

Thus,

\[
\lambda_{\text{max}} = 3.059585
\]

\[
CI = (3.058585 - 3)/(3 - 1) = 0.029793
\]

\[
CR = 0.029793/0.58 = 0.051366 = 5.1366\%
\]
As the consistency ratio is less than 10%, the inconsistency is acceptable.

Using the resultant matrix obtained by multiplying matrix $M$ by $M$ again say $M_1$ and the above steps are repeated again to obtain the revised weights so as to improve the consistency ratio.

$$M_1 = \begin{bmatrix} 2.9 & 7.25 & 22 \\ 1 & 2.9 & 9.5 \\ 0.55 & 1.1 & 3 \end{bmatrix}$$

Applying the same approach to matrix $M_1$, we obtain the following preferential weights:

$$\begin{bmatrix} 0.644113 \\ 0.254233 \\ 0.101655 \end{bmatrix}$$

Computing the difference of the previous normalizing values to this one, we get,

$$\begin{bmatrix} 0.001775 \\ -0.00199 \\ 0.000219 \end{bmatrix}$$

Upto 3 decimal place there is not much difference. So, we do not proceed further and assume the normalizing values obtained in first iteration for our further study.

Using the normalizing values used in equation (9), the weighted FGP is defined as:

$$\text{Maximize } 0.645888\mu_1 + 0.252239\mu_2 + 0.101874\mu_3$$

Subject to

All the constraints stated above in (6) and (7).

IV. RESULTS AND DISCUSSION

Solving the above problem by LINDO 11.0, we obtain the following results:

$$x_1 = 103.8732, x_2 = 136.3636, x_3 = 0,$$

$$x_4 = 75.53098, x_5 = 112.0134, x_6 = 119.9269,$$

$$\mu_1 = 0.1810699, \mu_2 = 1, \mu_3 = 1.$$  

The achievement level of the three goals is

$$G(1) = 567.2428, G(2) = 480, G(3) = 480.$$  

It may be noted that as previous solution of the FGP problem (which corresponds to equal importance of goals), in the present formulation WFGP of the G(2) and G(3) ($\mu_2$ and $\mu_3$) have achieved fully whereas the first goal G(1) with $\mu_1$ are achieved partially.

D. Preemptive Fuzzy Goal Programming Model:

In many decision problems the goals are not in the same measurable units, that is, they are commensurable. Further, sometimes the goals are such that unless a particular goal or a subset of goals is achieved, the other goals should not be considered. In such situations the weighting scheme of the previous section is not an appropriate method. The preemptive priority structure may be stated as $P_i \preceq P_{i+1}$ which means that the goals in the $i$-th priority level have higher priority than the goals in the $(i+1)$-th priority level, i.e., however large $N$ (a number) may be, $P_i$ cannot be equal to $NP_{i+1}$ by Ignizio [14], Sherali and Soyster [30].

Here the problem is subdivided into $k$ sub-problems, where $k$ is the number of priority levels. In the first sub-problem the fuzzy goals belonging to the first priority level have only been considered and solved using the simple additive model as described in Section 2.1. But at another priority levels the membership values achieved earlier for higher priority levels are imposed as additional constraints. In general the $i$-th sub-problem becomes:

$$\text{Maximize } \sum_p (\mu_i)_{p}$$

Subject to

$$\mu_s = \frac{G_s - L_s}{g_s - L_s},$$

$$AX \leq b$$
\[
(\mu)_r = (\mu^*)_r \\
r = 1, 2, ..., j - 1, \\
\mu_i \leq 1 \\
X, \mu_i \geq 0, i = 1, 2, ..., m
\]
where \((\mu_i)_r\) refers to the membership functions of the goals in the \(i\)-th priority level and \((\mu^*)_r\) is the achieved membership value in the \(r\)-th \((r \leq j - 1)\) priority level.

**Preemptive Fuzzy Goal Programming Problem:**

Now, using the weight matrix we apply preemptive FGP with

**Priority 1: Goal 2 and Goal 3**

**Priority 2: Goal 1.**

Goal 2 having more weightage than Goal 3 as specified by the matrix.

(i) **FGP with Priority 1:**

Maximize \[0.25 \cdot 2^2 + 0.10 \cdot 1^2 \cdot \mu_i\]

Subject to

All the constraints stated above in (6) and (7).

**RESULTS**

Solving the above problem by LINDO 11.0, we obtain the following results:

- \(x_1 = 81.18392\), \(x_2 = 45.2993\), \(x_3 = 150.2486\), \(x_4 = 57.91758\), \(x_5 = 112.0134\), \(x_6 = 132.7717\), \(\mu_1 = 0\), \(\mu_2 = 1\), \(\mu_3 = 1\)

The achievement level of the three goals is

\(G(1) = 560\), \(G(2) = 480\), \(G(3) = 480\).

(ii) **FGP with Priority 2:**

Maximize \(\mu_i\)

Subject to

- \(\mu_1 \leq 1\)
- \(\mu_2 = 1\)
- \(\mu_3 = 1\) with (6) excluding \(\mu_i \leq 1\) and (7).

**RESULTS**

Solving the above problem by LINDO 11.0, we obtain the following results:

- \(x_1 = 103.8732\), \(x_2 = 136.3636\), \(x_3 = 0\), \(x_4 = 75.53098\), \(x_5 = 112.0134\), \(x_6 = 119.9269\), \(\mu_1 = 0.1810699\), \(\mu_2 = 1\), \(\mu_3 = 1\)

The achievement level of the three goals is

\(G(1) = 567.2428\), \(G(2) = 480\), \(G(3) = 480\).

**V. CONCLUSION**

<table>
<thead>
<tr>
<th>FGP Model</th>
<th>Variables</th>
<th>(x_1) = 103.8732</th>
<th>(x_2) = 136.3636</th>
<th>(x_3 = 0)</th>
<th>(x_4 = 75.531)</th>
<th>(x_5 = 112)</th>
<th>(x_6 = 119.93)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Achieved Goal</td>
<td></td>
<td>(G_1 = 567.24)</td>
<td>(G_2 = 480)</td>
<td>(G_3)</td>
<td>(G_3 = 480)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Membership Values</td>
<td>(\mu_1 = 0.18)</td>
<td>(\mu_2 = 1.00)</td>
<td>(\mu_3 = 1.00)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Weighted FGP Model</th>
<th>Variables</th>
<th>(x_1) = 103.8732</th>
<th>(x_2) = 136.3636</th>
<th>(x_3 = 0)</th>
<th>(x_4 = 75.5309)</th>
<th>(x_5 = 112.013)</th>
<th>(x_6 = 119.9269)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Achieved Goal</td>
<td></td>
<td>(G_1 = 567.2428)</td>
<td>(G_2 = 480)</td>
<td>(G_3)</td>
<td>(G_3 = 480)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Membership</td>
<td>(\mu_1 = 0.1810699)</td>
<td>(\mu_2 = 1.00)</td>
<td>(\mu_3 = 1.00)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
It may be noted that as solution of the FGP problem (which corresponds to equal importance of goals) and in the formulation of WFGP, G(2) and G(3) with $\mu_2$ and $\mu_3$ have achieved fully whereas the first goal G(1) with $\mu_1$ are achieved partially. Also, we are getting the same results using the preemptive fuzzy goal programming (PFGP) technique where priority 1 given to goal 2 and goal 3 are fully achieved whereas priority 2 given to the achievement of goal 1 is partially achieved.

The difference between the goal programming problem applied and the result of either FGP or WFGP or PFGP is that in the previous case the daily profit is expected to be RM 582.98 under certainty whereas by applying any of the other methods stated above representing fuzziness, the daily profit is expected to be RM 567.2428.

The fuzzy goal programming model is found to be useful for small and medium enterprises to gauge their profits based on their labor, machine use and raw materials requirements with the aspiration levels to be imprecise in nature. The number of goals to be considered can also be increased based on the desirability of the decision maker in relation to their aspired objectives.

REFERENCES


