Application of fuzzy linear programming in construction projects

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ABSTRACT | In classical optimization model, the objective function and the constraints are represented very precisely under certainty. However, many of the constraints are externally controlled and the variations cannot be predicted to a reliable extent. This may cause difficulties in representing these interacting variables for optimization. To overcome these limitations, Zimmerman's fuzzy logic approach is applied for optimization in this paper. Here, the embedding simulation results are used as inputs to a fuzzy linear programming model to soften the notion of "*constraints*" and "*objective function*." This approach will acknowledge and postulate that the objective function and the constraints are of the same nature and the distinction between them is gradual rather than abrupt. An application of this integrated approach to a case study demonstrates the efficacy of this flexible algorithm in dealing with qualitative factors in a more meaningful way than classical linear programming. One of the main advantages of this method is that it can be easily implemented in the existing computer programs for optimization.

KEYWORDS | linear programming, fuzzy sets, tolerance limits, fuzzy goals, fuzzy constraints

1 Introduction

In civil engineering construction, complexities will often arise due to the presence of a large number of interacting variables and many of which may defy quantification. Nevertheless, construction engineers use different skills and strategies for accomplishing and resolving the constraints and achieving the tasks. Operations research (OR) techniques are widely used for construction management problems through different and appropriate mathematical models. One of the widely used tools of operations research in the construction industry is the linear programming technique. In this technique all the information pertaining to the problem is expressed in terms of linear constraints on the decision variables. Where the data is precise and the constraints are internally controlled, the technique is good for arriving at the optimized decision. On this basis feasible decisions are made in many project operations.

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In a real construction project, activities must be scheduled under limited resources, such as limited crew sizes, limited equipment amounts, and limited materials (Leu et al. 1999). However, many of these constraints are possibly externally controlled and these variations cannot be predicted to a reliable extent. For example, in a building project, the calculation of plinth area of quality with class 1, class 2, and class 3 comprises the decision variables, with the constraints of budget demand, municipal by-laws, etc. If there is a variation in the constraints, the variabilities cannot be easily taken care by classical linear programming for arriving at the values of decision variables. This has proved to be one of the most difficult aspects of linear programming, since this variation cannot be converted into mathematical equivalents. To adequately represent them by just keeping in the conventionally quantifiable variables is obviously a stumbling block. Consequently, the results could be erroneous as decision indicators. Thus, there is a need to accommodate these variations in the pre implementation stages of construction projects.

The aim of this paper is to use the fuzzy logic approach to represent the complexities of objective function and constraints. In this method, the problem has been formulated by converting the objective function into another constraint and flexibility is introduced in the problem. The approach described in this paper is intended to illustrate the practicability of applying fuzzy linear programming to civil engineering problem and the potential advantages of the resultant information.

2 Fuzzy set theory for optimization

The concept of fuzzy decision was first introduced by Bellman and Zadeh (1970). The imprecisely defined goals and constraints are represented as fuzzy sets in the space of alternatives (Sasikumar and Mujumdar 1998). According to Bellman and Zadeh (1970) in the conventional approach to decision-making, the principal ingredients of a decision process are: a set of alternatives, a set of constraints on the choice between different alternatives, and a performance function, which associates with each alternative. These ingredients have to be precisely defined to achieve the gain (or loss) in the decision process (Chuang and Munro 1983).

Zimmermann (1986) applied fuzzy set theory on linear optimization to develop a tool called fuzzy linear programming. This tool incorporates fuzziness in the objective function and constraints, and hence introduces flexibility in them. The objective function and constraints so formed are called fuzzy goal and fuzzy constraints, respectively. The *best* decision from the solution of the fuzzy linear programming lies within the range identified as optimal. It is accompanied by its membership value in the optimal range, which can be considered as a measure of the degree of acceptability of this best decision (Zadeh 1973).

3 Fuzzy linear programming

The theory of fuzzy sets will handle the form of uncertainty, which stems from the imprecise definition of boundaries of classes of objects (Lorterapong and Moselhi 1996). An important advance in utilizing this theory to decision making in a fuzzy environment is that, a decision is the confluence of goals and constraints.

In general the linear programming (LP) model is expressed mathematically in the form,

Maximize $Z = C^T x$

such that $Ax \le b$ .... (1)

and $x \ge 0$

where C^T = Transpose of Cost Coefficients
x = Decision Variables
A = Structural Coefficients
b = Constraints

C and x are n-vectors, b is an m-vector, and A is an (m x n) matrix.

The above model can be expressed into a fuzzy linear programming problem in the following form (Zimmerman 1996).

Find x such that

$$C^T x \gtrsim Z$$

$$Ax \lesssim b$$

and $$x \geq 0 \quad \text{.....................................(2)}$$

In fuzzy linear programming the objective function is expressed as a fuzzy set and the solution space which is defined by constraints is also modelled by fuzzy sets. Here "$\lesssim$" denotes the fuzzified version of "$\leq$" and has the linguistic interpretation "*essentially smaller than or equal to*." The objective function has been written as a minimizing goal with Z as upper bound. The flexibility in the constraints and the fuzziness in the objective functions are introduced into the conventional mathematical programming.

The flexibility and the fuzziness is represented by fuzzy sets, and are called "*fuzzy constraints*" and "*fuzzy goal*," respectively. Different parts of Eq. 2 can be considered fuzzy; and fuzziness can be expressed in different ways. The elements of A and C could be fuzzy numbers rather than crisp numbers. The constraints (b) could be represented by fuzzy sets rather than crisp inequalities. The objective function is represented by either a fuzzy set or a fuzzy function. The decision variables are considered to be only deterministic (or at most probabilistic). Then, the fuzzy objective function and the fuzzy constraints are characterized by their membership function. The aim is to satisfy both the goals and constraints (Bellman and Zadeh 1970).

By substituting $\begin{pmatrix} -C^T \\ A \end{pmatrix}$ and $\begin{pmatrix} -Z \\ b \end{pmatrix}$, then Eq. 2 becomes: (Zimmerman, 1996)

Find x such that

$$(Bx)_i \lesssim d_i \quad i = 1,.....,m+1 \quad \text{...................................(3)}$$

$$\text{and } x \geq 0$$

where x is an n-vector. Each of the m+1 rows are represented by fuzzy sets, and the membership function is $\mu_i(x)$, i = 1,......, m+1. $\mu_i(x)$ can be interpreted as the degree to which x fulfils (satisfies) the fuzzy inequality, $(Bx)_i \lesssim d_i$, where $(Bx)_i$ denotes the i[th] row of Eq. 3. An example of fuzzy constraint of fuzzy inequality $(Bx)_i \lesssim d_i$ is shown in Fig. 1.

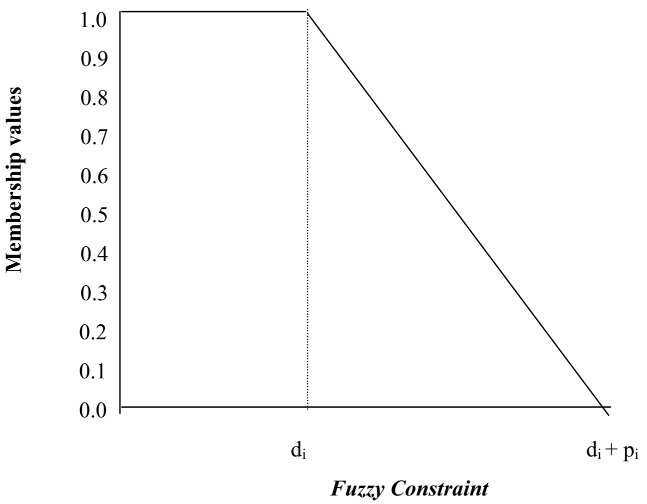

Figure 1. Fuzzy Inequality

In Fig. 1, d_i is the rigid constraint, and flexibility (p_i) is introduced in this constraint. Then membership value varies from 1 to 0 when constraint varies from d_i to d_i+p_i. Then the membership function of fuzzy set "*decision*" is (Bellman and Zadeh, 1970)

$$\mu_D(x) = \min_{i=1}^{m+1} \mu_i(x) \quad (4)$$

and the maximizing solution is

$$\mu_M(x^*) = \max \min_{i=1}^{m+1} (\mu_i(x)) \quad (5)$$

μ_i (x) will be '0' if the constraints are strongly violated, i.e., $(B)_i x > d_i + p_i$; and it is '1' if they are very well satisfied (i.e., satisfied in the crisp sense). μ_i (x) will increase or decrease monotonically from 0 to 1 between d_i and d_i+p_i. This is represented by the following Eq. 6.

$$\mu_i(x) = \begin{cases} 1 & \text{if } (B)_i x \leq d_i \\ 1 \text{ to } 0 & \text{if } d_i < (B)_i x \leq d_i + p_i \qquad i = 1, \ldots\ldots, m+1 \\ 0 & \text{if } (B)_i x > d_i + p_i \end{cases} \quad (6)$$

While using the simplest type of membership function, it is assumed to be linearly increasing over the "*tolerance interval*" (d_i, d_i+p_i). This tolerance interval represents a range of membership values acceptable to the decision maker with a linearly varying degree of satisfaction (Zimmermann 1996). This is represented in Eq. 7:

$$\mu_i(x) = \begin{cases} 1 & \text{if } (B)_i x \leq d_i \\ 1 - \dfrac{(Bx)_i - d_i}{p_i} & \text{if } d_i < (B)_i x \leq d_i + p_i \qquad i = 1, \ldots\ldots, m+1 \\ 0 & \text{if } (B)_i x > d_i + p_i \end{cases} \quad (7)$$

The p_i's are subjectively chosen constants of admissible violations of the constraints and the objective function. From Eq. 5 and Eq. 7 the maximizing decision becomes

$$\mu_M(x) = \max \min_{i=1}^{m+1} \left(1 - \frac{(B)_i x - d_i}{p_i} \right) \quad (8)$$

By introducing a new variable λ, which corresponds essentially to membership function of the fuzzy set "*decision*," the fuzzy linear programming problem becomes (Zimmerman 1996)

$$\begin{aligned} &\text{Maximize} && \lambda \\ &\text{such that} && \lambda p_i + (B)_i x \leq d_i + p_i, \; i = 1, \ldots, m+1 \\ &&& \lambda \leq 1 \\ &&& \lambda, x \geq 0 \end{aligned} \quad (9)$$

The optimal solution is the vector (λ^o, x^o), and this x^o is the maximizing solution of Eq. 5. This maximizing solution x^o is obtained by solving standard (crisp) LP with only one more variable λ and one more constraint than Eq. 1 (Zimmermann 1996).

Crisp constraints being special cases of fuzzy constraints, they can be directly incorporated in Eq. 9 as in the following: (Zimmermann 1996)

$$\begin{aligned} &\text{Maximize} && \lambda \\ &\text{such that} && \lambda p_i + (B)_i x \leq d_i + p_i, \; i = 1 \ldots m+1 \\ &\text{and} && Dx \leq b \\ &&& \lambda \leq 1 \\ &&& x, \lambda \geq 0 \end{aligned} \quad (10)$$

Another variable t_i is defined that measures the degree of violations of the i^{th} constraint. The membership function of the i^{th} row is then

$$\mu_i(x) = 1 - \frac{t_i}{p_i} \qquad \text{and } 0 \leq t_i \leq p_i$$

The crisp equivalent model is

$$\begin{aligned} &\text{Maximize} && \lambda \\ &\text{such that} && \lambda p_i + t_i \leq p_i, \; i = 1 \ldots m+1 \\ &&& (B)_i x - t_i \leq d_i \\ &&& t_i \leq p_i \\ &&& \lambda, x, t \geq 0 \end{aligned} \quad (11)$$

This foregoing model can be solved by the conventional simplex algorithm, and the solution will identify those values of the decision variables, which correspond to a maximizing decision (Zimmerman 1996).

4 Case study

An individual wishes to develop a 9290 sq.m. Commercial piece of property. Market studies indicate that the development should be rentable and that the available office space must not exceed 2 floors, stores must not exceed 1 floor, and living units must not exceed 3 floors for a walk up facility. The studies further indicate that, with in the sector of the city where the property is located, offices have a 20% vacancy rate, stores have a 5% vacancy rate and apartment units have a 10% vacancy rate (occupancy must not be less than 70% in order to obtain financial support from a funding agency).

Further building coverage should not exceed 30% of total lot area (2787 sq. m). Table 1 gives the rent/sq.m/year of each floor for each quality. A dash (–) indicates no construction, and Table 2 indicates the construction cost (Aguilar 1973).

Market rental preferences reveal that facility areas of individual types and qualities should not exceed 10%, 40%, and 25% for quality 1, 2, 3 of offices, 30% for quality 1 of stores, and 40%, and 30% of quality 1, 2 of apartments of total building area.

The budget shall not exceed $800,000 excluding cost of land. The objective of the case study is to maximize the rent under present market conditions.

4.1 Deterministic Linear Programming Formulation

The model formulation for this problem is

Let i = 1 offices, 2 stores, 3 apartments

j = 1 ground floor, 2 second floor, 3 third floor

k = 1 quality *a*, 2 quality *b*, 3 quality *c*

Here, x^k_{ij} is the floor area of facility type i, at level j, of architectural quality k. The quality 'k' refers the degree of architectural refinement of the space: type of finishes, environmental control, and many other considerations, the effect of which are reflected in the cost of construction and in the rentability of the facility.

Then from Table 1

- $x^k_{13} = 0$; k = 1,2,3
- $x^k_{21} = 0$; k = 2,3 and $x^k_{ij} = 0$; $i = 2$, $j=2,3$ *and* $k = 1,2,3$.
- $x^3_{3j} = 0$ j = 1,2,3

Table 1. Rent ($/sq.m./year)

Type	Level	Quality		
		a	b	c
1. Offices	1. Ground Floor	48.43	43.06	37.67
	2. Second Floor	43.06	57.86	32.29
2. Stores	1. Ground Floor	32.29	–	–
3. Apartments	1. Ground Floor	32.29	26.91	–
	2. Second Floor	32.29	26.91	–
	3. Third Floor	26.91	21.52	–

Table 2. Construction Cost ($/sq.m) Including Support Space

		Level		
		a	b	c
1. Offices	Ground Floor	204.52	182.99	139.94
	Second floor	193.75	161.46	139.94
2. Stores	Ground floor	118.40	–	–
3. Apartments	Ground floor	193.75	172.23	–
	Second floor	182.99	161.46	–
	Third floor	182.99	150.69	–

Herein, x^1_{11}, x^2_{11}, x^3_{11}, x^1_{12}, x^2_{12}, x^3_{12}, x^1_{21}, x^1_{31}, x^2_{31}, x^1_{32}, x^2_{32}, x^1_{33}, x^2_{33}, are denoted by x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, and x_{13} respectively, and are used in the following linear programming model. Based on the rent and vacancy rates of offices, stores, and apartments the objective function is

- Max $Z = 0.80\,(48.43\,x_1 + 43.06\,x_2 + 37.67\,x_3 + 43.06\,x_4 + 57.86\,x_5 + 32.29\,x_6) + 0.95\,(39.29\,x_7) + 0.90\,(32.29\,x_8 + 26.91\,x_9 + 32.29\,x_{10} + 26.91\,x_{11} + 26.91\,x_{12} + 21.52\,x_{13})$

which is the same as

- Max $Z = 38.74\,x_1 + 34.45\,x_2 + 30.14\,x_3 + 34.45\,x_4 + 46.29\,x_5 + 25.83\,x_6 + 37.33\,x_7 + 29.06\,x_8 + 24.22\,x_9 + 29.06\,x_{10} + 24.22\,x_{11} + 24.22\,x_{12} + 19.37\,x_{13}$

Constraints:

1. Construction cost

The lowest construction cost is $118.40 /sq. m., and an upper bound to the total building area is 800000/ 118.40 = 6757 sq. m. Therefore

- $x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 + x_{10} + x_{11} + x_{12} + x_{13} \leq 6757$

2. Market constraints

- $x_1 + x_4 \leq 676$
- $x_2 + x_5 \leq 2703$
- $x_3 + x_6 \leq 1689$
- $x_7 \leq 2027$
- $x_8 + x_{10} + x_{12} \leq 2703$
- $x_9 + x_{11} + x_{13} \leq 2027$

3. Site building area constraint

- $x_1 + x_2 + x_3 + x_7 + x_8 + x_9 \leq 2787$

4. Budget constraints

Under the assumption that the total number of floors in the building will be three, the budget constraint can be written as follows:

- $204.52x_1 + 182.99x_2 + 139.94x_3 + 193.75x_4 + 161.46x_5 + 139.94x_6 + 118.40x_7 + 193.75x_8 + 172.23x_9 + 182.99x_{10} + 161.46x_{11} + 182.99x_{12} + 150.69x_{13} \leq 800000$

The model is complete and LP optimization subject to constraints has been performed. Here, there are 9 constraint equations and 13 decision variables. The problem has been solved using LINGO 6.0. It is a simple tool which utilizes the power of linear and nonlinear optimization to formulate large problems concisely, solve them, and analyze the solution. The maximum expected rent is found to be $226,875.10 per annum ($f_1$) and optimum values of decision variables are

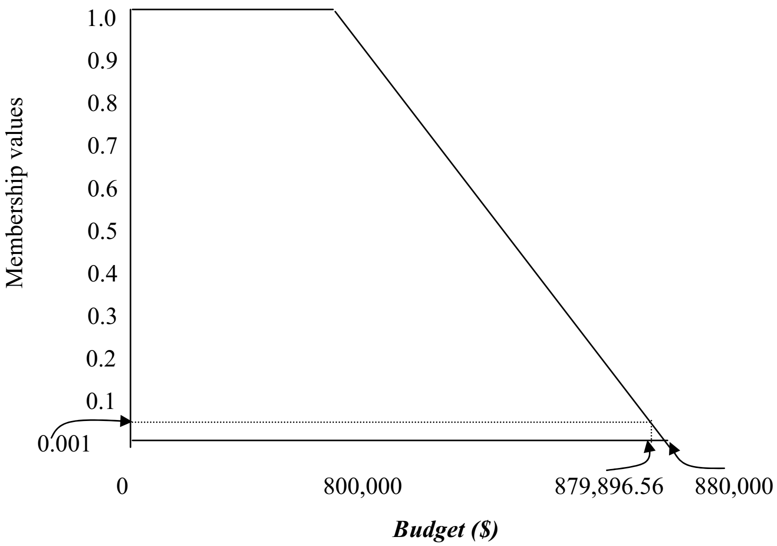

Figure 2. Budget Constraint

- $x_1 = 0.0$, $x_2 = 0.0$, $x_3 = 760.00$, $x_4 = 0.0$, $x_5 = 2703.00$, $x_6 = 123.07$, $x_7 = 2027.00$, $x_8 = 0.0$, $x_9 = 0.0$, $x_{10} = 0.0$, $x_{11} = 0.0$, $x_{12} = 0.0$, and $x_{13} = 0.0$.

The tolerance of 10% has been provided with respect to all the constraints and the values of flexibilities are $p_1 = 675$, $p_2 = 67$, $p_3 = 270$, $p_4 = 168$, $p_5 = 202$, $p_6 = 270$, $p_7 = 202$, $p_8 = 278$, and $p_9 = 80000$. The deterministic linear programming has been resolved by considering the above tolerances in the constraints to arrive at an optimum value (f_0) of $249,546.80. The optimum value for the model is fixed at $249,546.80. The difference of (f_0-f_1) determines the tolerance limit of the objective function i.e., $22,670. The objective function has been converted into another constraint equation with f_0 as an upper bound.

- $38.74\ x_1 + 34.45\ x_2 + 30.14\ x_3 + 34.45\ x_4 + 46.29\ x_5 + 25.83\ x_6 + 37.33\ x_7 + 29.06\ x_8 + 24.22\ x_9 + 29.06\ x_{10} + 24.22\ x_{11} + 24.22\ x_{12} + 19.37\ x_{13} \leq 249{,}546.80$

Now, the distinction between the goal (objective function) and the constraints has virtually disappeared. Attention has been confined to imprecision with respect to the goal (objective function) and stipulations (d_i), and it will be assumed that the coefficients of the structural matrix A are known with complete certitude.

The i[th] inequality of $(Bx)_i \leq d_i$ will be softened, in the sense that it is no longer mandatory to satisfy the inequality but necessary to satisfy the modified inequality

$$(Bx)_i \leq d_i + p_i$$

where p_i is a measure of the softness that has been introduced into the inequality. Now it is preferable to satisfy the original inequality. Some contravention of that inequality is acceptable until the softened inequality is fully taken up; however it is not permissible to admit any further relaxation beyond $d_i + p_i$.

The fuzziness in the constraints is illustrated in terms of tolerances allowed in the budget constraint. Initially, a firm constraint of $800,000 was placed on the budget. By introducing a tolerance of $80,000 ($p_9$), the decision maker is stating that the budget can vary from $800,000 to $880,000 with a linearly diminishing degree of acceptability.

Now the objective function and the constraint equations have been formulated into a single set of fuzzy inequalities. In fuzzy linear programming the membership values are derived for decision variables (x), and the minimum of these membership values represents the grade of membership $\mu_D(x)$. A new parameter 'λ' is introduced to satisfy the objective function and the constraints with respect to variations in 'x'.

The problem can be transformed to the following fuzzy linear programming model, which is equivalent to the model of Eq. 10.

Maximize λ

such that $\lambda (f_o - f_1) - Cx \leq -f_1$

$$\lambda p_i + Ax \leq b_i + p_i$$

$$Dx \leq b$$

$$\lambda \leq 1$$

$$\lambda, x \geq 0 \quad \text{.............................} (12)$$

Therefore the problem becomes
Max λ

- $22670 \lambda - 38.74 x_1 - 34.45 x_2 - 30.14 x_3 - 34.45 x_4 - 46.29 x_5 - 25.83 x_6 - 37.33 x_7 - 29.06 x_8 - 24.22 x_9 - 29.06 x_{10} - 24.22 x_{11} - 24.22 x_{12} - 19.37 x_{13} \leq -226875.10$
- $675\lambda + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 + x_{10} + x_{11} + x_{12} + x_{13} \leq 7432$
- $67\lambda + x_1 + x_4 \leq 743$
- $270\lambda + x_2 + x_5 \leq 2973$
- $168\lambda + x_3 + x_6 \leq 1857$
- $202\lambda + x_7 \leq 2229$
- $270\lambda + x_8 + x_{10} + x_{12} \leq 2973$
- $202\lambda + x_9 + x_{11} + x_{13} \leq 2229$
- $278\lambda + x_1 + x_2 + x_3 + x_7 + x_8 + x_9 \leq 3065$
- $80{,}000\lambda + 204.52x_1 + 182.99x_2 + 139.94x_3 + 193.75x_4 + 161.46x_5 + 139.94x_6 + 118.40x_7 + 193.75x_8 + 172.23x_9 + 182.99x_{10} + 161.46x_{11} + 182.99x_{12} + 150.69x_{13} \leq 880000$
- $\lambda \leq 1$
- and $x \geq 0, \lambda \geq 0$

The optimal solution to this fuzzy linear programming is $x_1 = 0$, $x_2 = 0$, $x_3 = 795.62$, $x_4 = 0.0$, $x_5 = 2829.55$, $x_6 = 129.28$, $x_7 = 2121.68$, $x_8 = 0.0$, $x_9 = 0$, $x_{10} = 0$, $x_{11} = 0.0$, $x_{12} = 0.0$, $x_{13} = 0$ and $Z = 237501.47$ with a value of 0.53 for λ. The original linearized objective function (Z) has the optimum value of \$226875.10. The '*best*' decision occurs at $x_3 = 795.62$, $x_5 = 2829.55$, $x_6 = 129.28$, $x_7 = 2121.68$, and $\lambda = 0.53$ resulting in an optimum value of \$237501.47, representing an increase of about 4.68%. This optimal solution obtained from the fuzzy linear programming, incorporates uncertainties in the objective function and constraints. The maximizing grade of membership is $\lambda = 0.53$; this value can be considered to be a measure of the degree of acceptability of this optimal decision.

5 Observations

The computational effort to determine the fuzzy set decision is larger than the crisp maximizing decision. Optimum decision in a fuzzy environment is the intersection of fuzzy constraints and fuzzy objective function. Since, it is a confluence of objective function and constraints, the acceptability values of the other constraints should not be less than 0.53. Using the budget constraint as an example, it can be seen that the total budget works out to be \$879,896.56 for the optimal decision. This exceeds the original constraint of \$800,000 by \$79,896.56 and the flexibility introduced for the constraint is \$80,000. But the fuzzy model accepts \$79,896.56 with an acceptability value of 0.53. Thus, the project needs an amount of \$879,896.56. The increase in the value of budget decreases the fuzzy membership value to 0.001 for an acceptability value of 0.53. Similarly, the membership values of the other constraint violations and acceptability values can also be computed.

It is seen from Table 3 that the variables x_3, x_5, x_6, and x_7 refers to class 3 facility for office of ground floor,

Table 3. Values of Decision Variables based on Deterministic and Fuzzy Linear Programming

Deterministic		Fuzzy	
$x_1 = 0.00$	$x_2 = 0.00$	$x_1 = 0.00$	$x_2 = 0.00$
$x_3 = 760.00$	$x_4 = 0.00$	$x_3 = 795.62$	$X_4 = 0.00$
$x_5 = 2703.00$	$x_6 = 123.07$	$x_5 = 2829.55$	$x_6 = 129.28$
$x_7 = 2027.00$	$x_8 = 0.00$	$x_7 = 2121.68$	$x_8 = 0.00$
$x_9 = 0.00$	$x_{10} = 0.00$	$x_9 = 0.00$	$x_{10} = 0.00$
$x_{11} = 0.00$	$x_{12} = 0.00$	$x_{11} = 0.00$	$x_{12} = 0.00$
$x_{13} = 0.00$	Z = $226,875.10	$x_{13} = 0.00$	Z= $237,501.47

class 2 facility for office of 2nd floor, class 3 facility for office of 2nd floor and class 1 facility for stores of ground floor. Fuzzy based linear programming solution gives higher values of plinth area for x_3, x_5, x_6 and x_7. Since the rent for class 2 facility of offices on the second floor is higher than the other facilities, the flexibility resulted in higher value of the objective function. The degree of acceptability of the optimal decision is related to the varying degree of acceptable ranges in constraint violations.

6 Conclusions

Construction projects are normally executed in an environment characterized by varying degrees of uncertainties. Since, the certainty, reliability and precision of the data is often illusory in the construction environment, the incorporation of vague and imprecise data into the OR techniques greatly contribute for the improvement of solution in most construction management problems. The major applications of fuzzy logic in the area of construction management are safety assessment of construction operations, tender evaluation, planning of river basins, selection and design of construction strategies, risk analysis, project scheduling, and working capital assessment. In addition, fuzzy logic can be successfully applied where human reasoning, human perception, or human decision making are involved.

In the first step of the interactive solution process, the system is modelled by using only the information, which the decision maker provides without any expensive acquisition. Knowing the first comprehensive solution, the decision maker can incorporate further information in the constraints and objective function to improve the optimality. This procedure, processes the information needed for the relevant components and thus reduces the construction costs.

The physical format of LP formulation is transformed into a fuzzy based LP format by converting into fuzzy goal, duly introducing flexibility into the constraints. By increasing the budget of $79896.56 the annual rent increases by $10626.37 and the solution is not sensitive to the design constraints imposed by the designer. Thus, the objective function value has increased by about 4.68% for the problem presented due to the application of fuzzy logic approach compared to the conventional LP approach. Various other design decisions are incorporated with equal ease. The flexibility introduced in the various constraints in the form of additional resources helps the decision maker to maximize the value of objective function.

The solutions obtained through this integrated approach are more realistic for deciding a proper course of decision making, although the computational effort is little more than that of deterministic solutions.

The acceptability value of 0.53 indicates, the degree to which each constraint is satisfied under the uncertain conditions, thus allows decision maker to identify the needed flexibility for various constraints. Further research work is required to validate the findings and to determine globally guaranteed values of tolerance limits for different constraints.

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