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Genetic Algorithm Based Hybrid Approach to Solve Optimistic, Most-likely and Pessimistic Scenarios of Fuzzy Multi-objective Assignment Problem Using Exponential Membership Function

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

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Abstract

This paper discussed a genetic algorithm based hybrid approach to solve different scenario (optimistic scenario, most-likely scenario and pessimistic scenario) of fuzzy multi-objective assignment problem (FMOAP) using an exponential membership function in which coefficient of the objective function is described by triangular possibilities distribution (TDP). Moreover, we used the α-level sets to classify the fuzzy judgment for Decision maker (DM) to optimize different scenario of fuzzy objective functions. We used a fuzzy technique to solve multi-objective optimization problem in which DM is required to specify the indistinct aspiration level as per the his/her preference and genetic algorithm is used to solve the 0-1 optimization problem for different choices of shape parameter in the exponential membership function. A numerical example is provided to demonstrate the effectiveness of the proposed approach with data set form realistic situation.

Keywords: Assignment problem; α-level sets; optimistic scenario, most likely scenario; pessimistic scenario; exponential membership function; genetic algorithm.

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1 Introduction

In real world decision making scenario, several organizations faced with one important problem of allocating the different employees to different jobs. Each employee may spend different quantity of resources to complete different jobs because of the personal ability or other reasons. The objective is to assign each job to proper employee so that the total utilization of resources can be optimized and all jobs can be completed. Assignment problem (AP) deals with assigning the N employees to N jobs such that total cost/ time can be minimized and total profit/ quality can be maximized. (With various consumption rates). In AP, generally two types of objectives are measured: Maximize objective and Minimize objective. Minimization used minimize job cost or total duration etc while the maximization used for maximize overall profit or the overall quality etc. The general solution procedures of AP can be found in the literature survey of Pentico [1].

In the real world decision making, we may often meet uncertain phenomena such as random phenomena, fuzzy phenomena, and so on due to the uncertainty. In such conditions, AP turns into an uncertain assignment problem as fuzzy assignment problem (FAP). [2] first time introduced the concept fuzzy set theory which provided high effectual way to handle uncertain data. In decision making problem of real world, AP has more advantage by fuzzy theory, subjective preference of decision maker (DM). One may refer to the articles ([3],[4],[5],[6],[7],[8],[9],[10],[11], [12], [13], [14], [15]) for more details on FAP. In decision making area, fuzzy concept is mostly used in multi-objective optimization problem (MOP). One may refer to the article ([16],[17], [18], [19]) for more details on MOP.

Possibilistic decision-making models have given an important characteristic in handling objective functions and constraints of vague coefficients and manage vague information of real world decision making problems. Several studies in the literature are focused on fuzzy objective function and/or constrains. With respect to possibilities decision making model, one may refer to the articles of ([20],[21], [13],[22], [23], [24], [25]).

FMOAP is a single 0-1 optimization problem with some realistic constraints and is NP-hard problem. To concern with such kind of problem, several methods have been developed by researchers. Reference [26] has proposed a hybrid genetic algorithm to solve bi-criteria assignment problem in which this algorithm is a cooperative approach between genetic algorithm and linear programming method to generate the set of non supported efficient solutions of the problem and it also contains local search procedure to introduce for balancing the diversification and the intensification in the search area. Reference [27] proposed the GA based hybrid approach to solve multi-objective assignment problem. Toroslu and Arslanoglu [28] presented GA solutions for different versions of the personnel assignment problem with multiple objectives based on hierarchical and set constraints. Reference [29] used GA to solve personal assignment problem with verbal information. The Three Index Assignment Problem (AP3) is studied by Gaofeng Huang et al. [30] proposed a new local search heuristic for Three index assignment problem and hybridized it with genetic algorithm. Reference [31] solved assignment problem using GA and simulated annealing method. Harper et al. [32] used genetic algorithm for the project assignment problem. Yonghui Oh et al [33] solved A dock-door assignment problem for the Korean mail distribution center by two solution methods, three-phase heuristic procedure and GA. Harish Garg [34] has presented a hybrid technique as PSO-GA for solving constrainted optimization problem.

In this paper, we proposed genetic algorithm based hybrid approach to solve different scenario (optimistic scenario, most-likely scenario and pessimistic scenario) of FMOAP using fuzzy exponential membership function. Fuzzy technique is most commonly used to solve multi-objective optimization problem in which decision maker (DM) is require to specify the indistinct aspiration level based on his past experience and information for find the optimal allocations plan. GA provided a proper technique to solve the non-linear, discrete, non-convex types of large scale optimization problem. Genetic algorithm based hybrid approach gives the great flexibility to solve multi-objective optimization problem in terms of considered the different choices of aspiration level for each objective function. This approach forces to optimize each objective by maximized the degree of satisfaction in respect of cost, time and quality objective to provide better assignment plans.

The rest of the paper is as follows. Section-2 described the formulation of fuzzy multi-objective assignment problem. Section-3 gives a discussion of possibilistic programming approach, formulation of auxiliary multi-objective 0-1 programming model for optimistic, most-likely and pessimistic scenarios. Section-4 discussed Solution method, algorithm and flow chart for auxiliary model. Numerical illustration and obtained results analysis are discussed in section-5 to show the effectiveness of developed hybrid approach in different situation as per scenario. Finally, in section-6, we submit our conclusion.

2 Fuzzy Multi-objective Assignment Problem Formulation

Main characteristics and some assumption are used in the fuzzy multi-objective assignment problem (FMOAP) are **(1)** Each job is finished by only one employee, and an employee can accept more than one job, all the jobs must be completed. **(2)** It is not compulsory to allow any job to some employees. **(3)** It is necessary to specify the number of employees who have been assigned to jobs, to balance the amount of work between the employees. **(4)** In the decision-making method, each employee is considered by his/her working ability ([12],[13]). We assume that each employee should be assigned the number of duties in a certain range.

2.1 Fuzzy multi-objective assignment model

To formulate the mathematical model of FMOAP, the indices, parameters and variables are used as per ([12],[13]). **(1) Parameters:** workers = jobs = n; number employees assigned jobs = s; maximum jobs assigned to each employee $=l_i$; **(2) Indices:** j and i respectively defined index of jobs and employee **(3) Decision variables:** x_{ij} is represented the whether the i$^{\text{th}}$ employee is assigned for j$^{\text{th}}$ jobs or not. $x_{ij} = \begin{cases} 1; & \text{if i}^{\text{th}} \text{ employee is assigned to j}^{\text{th}} \text{ job} \\ 0; & \text{otherwise} \end{cases}$

Formulation of objective functions:

After completion of all jobs, the total cost, total consumed time and the total achieved a quality level are given as follows:

$\widetilde{z_1} = \sum_{i=1}^{n}\sum_{j=1}^{n} \widetilde{c_{ij}} x_{ij},\ \widetilde{z_2} = \sum_{i=1}^{n}\sum_{j=1}^{n} \widetilde{t_{ij}} x_{ij},\ \widetilde{z_3} = \sum_{i=1}^{n}\sum_{j=1}^{n} \widetilde{q_{ij}} x_{ij}$

In this problem, quality rating of linguistic variables: 'Good', 'Medium good', 'Fair', 'Medium poor', 'poor' are considered as (0,1,3), (1,3,5), (3,5,7), (5,7,9), (7, 9,10) respectively. At the different five levels, the quality of the completed jobs has been considered, where "good" and "poor" level are best and worst respectively i.e. shifting from "good" to "poor", the concentration of quality decreases while related fuzzy values raises. In order to maintain uniformity of objective functions it is necessary to minimize quality objective function [13].

Model constraints

noindent As per the mentioned description of FMOAP, the constraints are formulated as follows:

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij} = n \tag{2.1}$$

$$\sum_{i=1}^{n} x_{ij} = 1, \;\; j = 1, 2, ..., n \tag{2.2}$$

$$\sum_{j=1}^{n} x_{ij} \leq l_i \,; \;\; i = 1, 2, ..., n \tag{2.3}$$

$$\sum_{i=1}^{n} \min\left\{1, \sum_{j=1}^{n} x_{ij}\right\} \geq s \tag{2.4}$$

$$x_{ij} \in \{0, 1\}\,, \; i = 1, 2, ..., n, \;\; j = 1, 2, ..., n. \tag{2.5}$$

2.2 Decision problem

The fuzzy multi-objective assignment problem is now formulated as follows:
(Model-1)
$(\widetilde{z_1},\, \widetilde{z_2},\, \widetilde{z_3}) = \left(\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} \widetilde{c_{ij}} x_{ij}, \;\; \sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} \widetilde{t_{ij}} x_{ij}, \;\; \sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} \widetilde{q_{ij}} x_{ij} \right)$
Subject to: (2.1) to (2.5)

3 Possibilistic Programming Approach

The collection data on real world problems generally involve some type of uncertainty. As a matter of fact, many pieces of information cannot be quantified due to their nature. These types of the incomplete data are modeled by possibility distribution ([35], [36],[18], [30], [37] [10], [21], [22], [14]). We convert the FMOAP model into an auxiliary crips multi-objective optimization (CMOP) model by the Possibilistic approach [13]. In real world DM construct the TPD by using the (c_i^m),(c_i^o) and

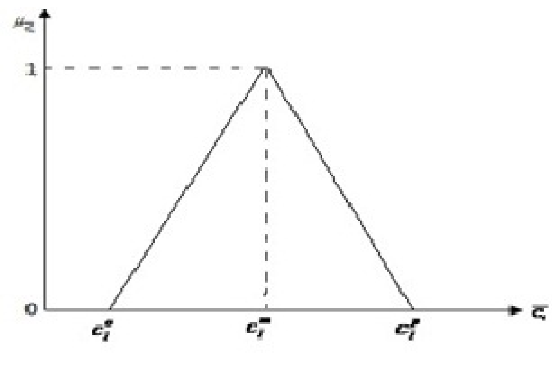

Fig. 1. TPD of c_i

(c_i^p), most possible value, the most optimistic value and the most pessimistic value respectively.

3.1 Formulation of multi-objective 0-1 programming model

Objective function cost with the triangular Possibilistic distribution is defined as $(z_1^m, 1)$,$(z_1^p, 0)$, and $(z_1^o, 0)$ and it described as

$$\begin{aligned}&\min\ \widetilde{z_1} = \min(z_1^o, z_1^m, z_1^p) = \sum_{i=1}^{n}\sum_{j=1}^{n}\widetilde{c_{ij}}x_{ij} = \\ &\min\left(\sum_{i=1}^{n}\sum_{j=1}^{n}c_{ij}^o x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}c_{ij}^m x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}c_{ij}^p x_{ij}\right)\end{aligned} \tag{3.1}$$

where $c_{ij} = \left(c_{ij}^o, c_{ij}^m, c_{ij}^p\right)$, which can be considered as follows.

$$(\min\ z_{11},\ \min\ z_{12},\ \min\ z_{13}) = \left(\sum_{i=1}^{n}\sum_{j=1}^{n}c_{ij}^o x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}c_{ij}^m x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}c_{ij}^p x_{ij}\right) \tag{3.2}$$

Eq.(3.2) is associated with optimistic scenario, the most likely scenario and the pessimistic scenario respectively.

Using the α-level sets concepts $(0 \le \alpha \le 1)$, each c_{ij} can be stated as$(c_{ij})_\alpha = \left((c_{ij})_\alpha^o, (c_{ij})_\alpha^m, (c_{ij})_\alpha^p\right)$, where$(c_{ij})_\alpha^o = c_{ij}^o + \alpha\left(c_{ij}^m - c_{ij}^o\right),\ (c_{ij})_\alpha^m = c_{ij}^m,\ (c_{ij})_\alpha^p = c_{ij}^p - \alpha\left(c_{ij}^p - c_{ij}^m\right)$.
Hence, Eq.(3.2) can be written as:

$$(\min\ z_{11},\ \min\ z_{12},\ \min\ z_{13}) = \left(\sum_{i=1}^{n}\sum_{j=1}^{n}(c_{ij})_\alpha^o x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}(c_{ij})_\alpha^m x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}(c_{ij})_\alpha^p x_{ij}\right) \tag{3.3}$$

Similarly, MOP model of time and quality objective function are as follows.

$$(\min\ z_{21},\ \min\ z_{22},\ \min\ z_{23}) = \left(\sum_{i=1}^{n}\sum_{j=1}^{n}(t_{ij})_\alpha^o x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}(t_{ij})_\alpha^m x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}(t_{ij})_\alpha^p x_{ij}\right) \tag{3.4}$$

$$(\min\ z_{31},\ \min\ z_{32},\ \min\ z_{33}) = \left(\sum_{i=1}^{n}\sum_{j=1}^{n}(q_{ij})_\alpha^o x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}(q_{ij})_\alpha^m x_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{n}(q_{ij})_\alpha^p x_{ij}\right) \tag{3.5}$$

Here, α-levels be a sign of DM confidence with respect to fuzzy judgments, some time called as confidence levels [13].

3.2 Auxiliary multi-objective 0-1 programming model with different scenario

To generate the following multi-objective 0-1 programming model with different scenario, crisp multiple objective functions are used.

Model-2:

For optimistic scenario:

$$\begin{aligned}&(\min\ z_{11}, \min\ z_{21}, \min\ z_{31}) = \left(\sum_{i=1}^{n}\sum_{j=1}^{n}(c_{ij})_\alpha^o x_{ij}, \sum_{i=1}^{n}\sum_{j=1}^{n}(t_{ij})_\alpha^o x_{ij}, \sum_{i=1}^{n}\sum_{j=1}^{n}(q_{ij})_\alpha^o x_{ij}\right)\\ &\text{under the constraints } (2.1) - (2.5)\end{aligned} \tag{3.6}$$

For most likely scenario:

$$\begin{aligned}&(\min\ z_{12}, \min\ z_{22}, \min\ z_{32}) = \left(\sum_{i=1}^{n}\sum_{j=1}^{n}(c_{ij})_\alpha^m x_{ij}, \sum_{i=1}^{n}\sum_{j=1}^{n}(t_{ij})_\alpha^m x_{ij}, \sum_{i=1}^{n}\sum_{j=1}^{n}(q_{ij})_\alpha^m x_{ij}\right)\\ &\text{under the constraints } (2.1) - (2.5)\end{aligned} \tag{3.7}$$

For pessimistic scenario:

$$(\min\, z_{13}, \min\, z_{23}, \min\, z_{33}) = \left(\sum_{i=1}^{n} \sum_{j=1}^{n} (c_{ij})_{\alpha}^{m} x_{ij}, \sum_{i=1}^{n} \sum_{j=1}^{n} (t_{ij})_{\alpha}^{m} x_{ij}, \sum_{i=1}^{n} \sum_{j=1}^{n} (q_{ij})_{\alpha}^{m} x_{ij} \right) \quad (3.8)$$

under the constraints (2.1) − (2.5)

4 Solution Method for Auxiliary Model

To characterize the indistinct aspiration level of the DM, fuzzy membership functions like linear, piecewise linear, exponential, tangent etc. are used. Out of them linear membership function is mostly used because it is defined by two fixing points: upper bound and lower bound of the objective and also considered only a violent calculation of real world circumstances. Additionally, membership function is used for describing the behavior of uncertain values. In such situation, non linear membership function is offered healthy representation then others as to reflect the reality as the marginal rate of increase of membership values as function of model parameter is not constant [13].

GA is a most adaptive optimization search methodologies based on machine of natural genetics, natural selection and survival of fitness in biological system. It is work by mimicking the evaluating principle and chromosome processing in natural genetics ([32], [29], [30], [33], [38], [31], [28]). For find the solution of FMAOP of single optimization by GA, first encode chromosomes according to problem and define fitness function to measure the chromosomes. Thereafter apply three operators, selection, crossover and mutation to generate the new population. Selection process is forming a parent population for creating the next generation. Crossover process is the process of selecting two parents of chromosomes and produces a new offspring chromosome. Mutation process is process with mutation rate randomly alter selected positions in a selected chromosome. Thus the new population is generated by replacing some chromosomes in the parent population with the children population which is useful for find efficient solution of FMOAP [31].

This section presented genetic algorithm based hybrid approach for optimistic, most-likely and pessimistic scenario FMOAP to determine the best efficient solution with use of exponential membership function to characterize the indistinct aspiration levels of DM.

4.1 Steps to find the solution of FMOAP using genetic algorithm based approach

The step-wise description of the proposed genetic algorithm based approach to find the assignment plans of optimistic, most-likely and pessimistic scenario of the FMOAP is as follows:

Step-1: Formulate the model-1 of FMOAP, using appropriate triangular possibilities distribution.
Step-2: According to a confidence level α, define the corps objective function model (model-2).
Step-3: Find out the positive ideal solution (PIS) and negative ideal solution (NIS) [[13]] for each objective function of the model-2.
Step-4: Find fuzzy exponential membership value for z_{ij} (i=1, 2, 3; j=1, 2, 3).

$$\mu_{z_{ij}}^{E}(x) = \begin{cases} 1; & \text{if } z_{ij} \le z_{ij}^{\text{PIS}} \\ \frac{e^{-S\psi_{ij}(x)} - e^{-S}}{1-e^{-S}}, & \text{if } z_{ij}^{\text{PIS}} < z_{ij} < z_{ij}^{\text{NIS}} \\ 0\,; & \text{if } z_{ij} \ge z_{ij}^{\text{NIS}} \end{cases} \quad (4.1)$$

Where, $\psi_{ij}(x) = \frac{z_{ij} - z_{ij}^{\text{PIS}}}{z_{ij}^{\text{NIS}} - z_{ij}^{\text{PIS}}}$ and S is non-zero shape parameter given by DM that $0 \le \mu_{Z_{ij}}(x) \le 1$. For $S > 0\,(S < 0)$, the membership function is strictly concave (convex) in $[z_{ij}^{\text{PIS}}, z_{ij}^{\text{NIS}}]$. The value of

the fuzzy membership function allows us to model the grades of precision in corresponding objective function [2].
Step-5: In step-5, fuzzy membership functions are comprehensive by using the product operator. Thus, FMOAP can be written in the single-objective optimization (SOP) problem with different scenarios are as follows:

(Model-3)

Optimistic scenario:

$$\begin{array}{l} \max\, W = \prod_{i=1}^{3} \prod_{j=1} \mu_{Z_{ij}} \\ undertheconstraints (2.1) to (2.5) \\ \mu_{Z_{i1}}(x) - \overline{\mu_{Z_{i1}}}(x) \geq 0;\ i = 1,\, 2,\, 3 \end{array} \tag{4.2}$$

Most-likely scenario:

$$\begin{array}{l} \max\, W = \prod_{i=1}^{3} \prod_{j=2} \mu_{Z_{ij}} \\ undertheconstraints (2.1) to (2.5) \\ \mu_{Z_{i2}}(x) - \overline{\mu_{Z_{i2}}}(x) \geq 0;\ i = 1,\, 2,\, 3 \end{array} \tag{4.3}$$

Pessimistic scenario:

$$\begin{array}{l} \max\, W = \prod_{i=1}^{3} \prod_{j=3} \mu_{Z_{ij}} \\ undertheconstraints (2.1) to (2.5) \\ \mu_{Z_{i3}}(x) - \overline{\mu_{Z_{i3}}}(x) \geq 0;\ i = 1,\, 2,\, 3 \end{array} \tag{4.4}$$

where $\overline{\mu}_{Z_{ij}}(x)$; $i = 1, 2, 3$; $j = 1, 2, 3$ is the desired aspiration level of fuzzy goals corresponding to each objective. The above model can be solved for varying aspiration levels of the DM regarding the achievement of various fuzzy membership functions [12].
Step-6: To deal with the single-objective optimization problem model-3 of FMOAP, genetic algorithm (GA) is used with different choices of the shape parameter.

- **Encoding of Chromosomes:**
  In order to form of solution of FMOAP, it is necessary to consider a data structure of chromosomes, which represents the solution of problem in encoding space. In encoding space, we set 0's to all $n \times n$ gene of a chromosomes then for randomly chosen a gene of chromosome, we set 1's in each column exactly one and in each row less or equal to l_i according to model which satisfy constraints (1) to (5) of model-3. Each component in the string (chromosome) can be uniquely expressed as 2^r; where r is real value varying from 0 to n-1.

- **Evaluate the fitness function:**
  In GA, the fitness function is a major question for solving FMOAP. Evaluate the objective function of model-3 which satisfies the only constraints (14) to (16) because infeasibility will lead by the constraints (14) to (16) and the structure of chromosomes takes care of the constraints (5) to(1) .

- **Selection:**
  The selection operator is used to determine which chromosome in current population will

be used to reproduce new child for next population who will have highest fitness. It is carefully formulated the chromosomes of population with highest fitness of being selected for mutation/ next generation. It improves the average quality of the chromosomes of the population for the next generation by giving the highest quality chromosomes a better chance to get copied into ([38], [31]).

In this paper, we used tournament selection to find the solution of FMOAP due to its efficiency and easy implementation. In tournament selection, N chromosomes are selected randomly from the population and compare against each other. The chromosome with the highest fitness (winner) will select for the next generation and others are disqualified for the next generation. This selection is continued until the number of winner equal to population size.

- **Crossover:**
  After successfully completion of tournament selection, the crossover operator is used to produce a new offspring for the next generation. The scheme behind the crossover is that offspring may have better fitness then the both of the parent if it takes better characteristic from each parent.

  For FMOAP, We have used two point crossover to generate new offspring. In two point crossover, exchange the gene values between the randomly two crossover points in two selected parent chromosomes to generate the new offspring [38].

- **Construct the threshold**:
  To maintain the diversity in population after crossover, construct the threshold for FMOAP's solution. In this step, we have parenthood population and childhood population out which they are selected for the new iteration.

  For constructing the threshold, once method of selecting the population may be to display the whole population in ascending order of their objective function value and choose predetermined individual strings from each category. For that we divide the population in four categories: those having values above $\mu + 3 * \sigma$, values between $\mu + 3 * \sigma$ and μ, values between μ and $\mu - 3 * \sigma$, and values less than $\mu - 3 * \sigma$. In this way the best string cannot be escaped ([27, 31]).

- **Mutation:**
  For the recovering the lost genetic materials as well as for randomly disturbing genetic information, mutation operator is applied. In this paper, we apply swap mutation ([27], [38],[31]) out of numerous available mutation operators. In swap mutation, two random spots are chosen in a string and swapping corresponding values at position.

  If we swap the string $< 1, 2, 3, 4, 5 >$at second and fourth position then the new mutate string become $< 1, 4, 3, 2, 5 >$

- **Termination criteria:**
  When the algorithm has run a given number of iterations, it stops and gives output as the best solution. This iteration process is repeated until a termination condition has been reached.

After developing the algorithm, two cases are implemented: one in which mutation is used and another in which mutation is not used. In both cases the answer converged to the efficient solution for FMOAP [27].

If obtained solution is accepted by DM then considers it as the ideal compromise solution and stop solution process else change value of and repeat the steps 2 to 5 till satisfactory solution achieved.

4.2 Algorithm

Input: *Parameters:* $(Z_1, Z_2, ..., Z_m, n)$
Output : *To find the solution of FMOAP*
Solve FMOAP $(Z_k \downarrow, X \uparrow)$

begin

read: *example*
while *example = FMOAP do*
for *k=1 to m do*
enter matrix Z_k

end

-|*find triangular possibilities distribution for each objective function.*
-|*define the crips multi-objective assignment problem according to* $\alpha-$ ***level***
-|*determine the positive ideal solution and negative ideal solution for each objective.*
for *k=1 to m do*
$z_{ij}^{\text{PIS}} = \min\ (z_i)_{\alpha}^{0}\ ,\ i, j = 1,\ 2,\ 3$
Subject to constraints (2.1) to (2.5)

end

for *k=1 to m do*
$z_{ij}^{\text{NIS}} = \max\ (z_i)_{\alpha}^{0}\ ,\ i, j = 1,\ 2,\ 3$
Subject to constraints (2.1) to (2.5)

end

-|*Define exponential membership function for each objective.*
for *k=1 to m do*

$$\mu_{z_{ij}}^{E}(x) = \begin{cases} 1; & \text{if } z_{ij} \le z_{ij}^{\text{PIS}} \\ \frac{e^{-S\psi_{ij}(x)} - e^{-S}}{1-e^{-S}}, & \text{if } z_{ij}^{\text{PIS}} < z_{ij} < z_{ij}^{\text{NIS}} \\ 0\,; & \text{if } z_{ij} \ge z_{ij}^{\text{NIS}} \end{cases}$$

end

-|*find single objective optimization model under given constraints from MOP model according to different scenario.*
For *k=1 to m do*

$$\max W = \prod_{i=1}^{3} \prod_{j=1}^{3} \mu_{Z_{ij}}$$

Subject to:
Constraints (2.1) to (2.5)

End

|- *find the solution SOP using GA*

Procedure: *GA*

Begin

Generation=0;
P= Generate the initial population of solution.
For *$(X \in P)$*
Evaluate Z(X); (Z(X) is objective function of X.)

end

While *(Stopping criterion not met)*
{*Generation=Generation+1;*

Begin

-|*Apply tournament selection;*
For $P' \in P$
P'=select fitness individual from P for matting pool according to tournament selection.
$P" = \phi$
end

Repeat (Until enough children produced)
For $P_1, P_2 \in P'$
Select P_1 and P_2 from P'.
Apply the two point crossover on P_1 and P_2 for produced new offspring. $P" = P" \cup X$ child;

end

Repeat
For $X \in P''$
Make a threshold, to keep the best individuals.
end
For $X \in P''$
Apply inversion on X.

End (Begin)

P=P";
end *(**while**)*
end (Begin)
end

4.3 Flowchart

Fig. 2. shows the flowchart of the solution procedure of FMAOP :

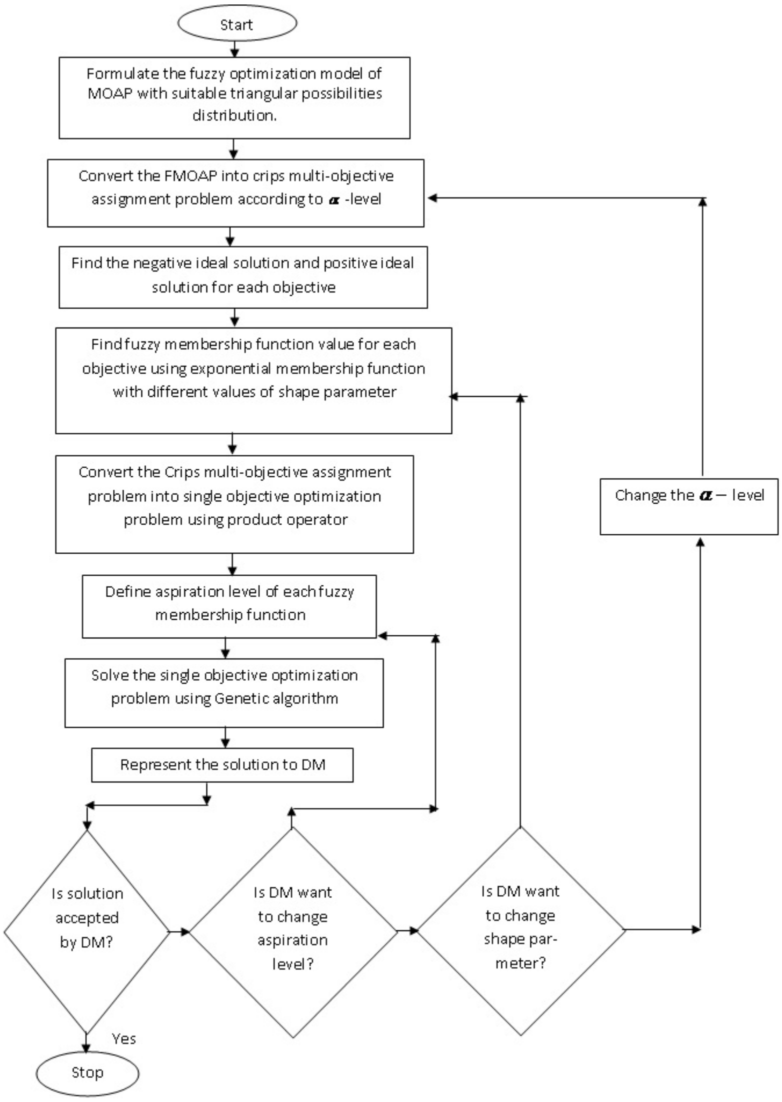

Fig. 2. Flowchart of the solution procedure of FMAOP

5 Numerical Illustration and Result Analysis

To justify proposed method, numerical illustration of FMOAP has been refereed from the article of the Pankaj and Mukesh [13] which shown in Table-1. To evaluate fuzzy cost-time-quality objective assignment problem, the model is coded. It is solved by Matlab and all tests are carried out on an Intel (R)-core i5 CPU@ 2.60 GHz computer with 4 GB of RAM. The primary attributes for solving the problems summarized as follows: Number of workers = Number of jobs = 6, l_i= 2, s= 4, population size=1000, iterations=100.

Table 1. Cost-time-quality matrix

Worker(i)	Job(j)						
		Job-1	Job-2	Job-3	Job-4	Job-5	Job-6
Worker -1	c_{ij}	(4,6,8)	(3,4,6)	(4,5,8)	(6,8,11)	(7,10,14)	(4,6,7)
	t_{ij}	(2,4,5)	(16,20,24)	(7,9,12)	(2,3,5)	(5,8,10)	(7,9,12)
	q_{ij}	(0,1,3)	(1,3,5)	(0,1,3)	(0,1,3)	(0,1,3)	(3,5,7)
Worker -2	c_{ij}	(4,6,7)	(4,5,7)	(5,6,9)	(3,5,7)	(6,9,11)	(6,8,11)
	t_{ij}	(4,6,9)	(15,18,22)	(6,8,12)	(5,7,10)	(14,17,20)	(6,8,10)
	q_{ij}	(1,3,5)	(3,5,7)	(1,3,5)	(3,5,7)	(5,7,9)	(3,5,7)
Worker -3	c_{ij}	(8,11,14)	(5,7,9)	(2,4,6)	(5,8,12)	(2,3,4)	(3,4,6)
	t_{ij}	(2,3,4)	(6,8,10)	(17,20,24)	(5,7,10)	(12,15,18)	(5,7,10)
	q_{ij}	(0,1,3)	(5,7,9)	(3,5,7)	(1,3,5)	(3,5,7)	(5,7,9)
Worker -4	c_{ij}	(7,9,12)	(7,10,12)	(6,8,11)	(4,6,8)	(8,10,12)	(3,4,6)
	t_{ij}	(10,12,16)	(10,13,16)	(12,14,18)	(4,6,9)	(7,9,12)	(8,10,14)
	q_{ij}	(3,5,7)	(7,9,10)	(1,3,5)	(3,5,7)	(1,3,5)	(1,3,5)
Worker -5	c_{ij}	(3,4,6)	(4,6,8)	(5,7,10)	(7,9,12)	(6,8,12)	(5,7,10)
	t_{ij}	(7,9,12)	(5,8,11)	(5,7,10)	(11,14,18)	(3,5,8)	(7,9,12)
	q_{ij}	(1,3,5)	(7,9,10)	(5,7,9)	(3,5,7)	(1,3,5)	(1,3,5)
Worker -6	c_{ij}	(2,3,4)	(4,5,7)	(8,11,15)	(8,10,13)	(9,12,15)	(6,8,12)
	t_{ij}	(14,17,21)	(10,13,16)	(2,3,5)	(3,5,8)	(10,13,17)	(5,7,10)
	q_{ij}	(1,3,5)	(1,3,5)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)

Table-2 gives the PIS and NIS for each objective functions for $\alpha = 0.1$, $\alpha = 0.5$ and $\alpha = 0.9$. These values are used to define the exponential membership function. The corresponding values are obtained in below table.

Table 2. PIS and NIS for fuzzy objective functions

$\alpha-$ level	Solutions	Objectives								
		z_{11}	z_{12}	z_{13}	z_{21}	z_{22}	z_{23}	z_{31}	z_{32}	z_{33}
$\alpha = 0.1$	PIS	15.8	23	32	20	29	40.7	3.9	12	22.8
	NIS	46.6	61	77.2	81.8	98	118.7	31.2	42	51.9
$\alpha = 0.5$	PIS	19	23	28	24	29	35.5	7.5	12	18
	NIS	53	61	70	89	98	109.5	36	42	47.5
$\alpha = 0.9$	PIS	22.2	23	24	28	29	30.3	11.1	12	13.2
	NIS	59.4	61	62.8	96.2	98	100.3	40.8	42	43.1

Further, we present the sensitivity analysis by considering an optimistic scenario, most-likely scenario, and pessimistic scenario of each objective individually. According to triangular possibility distribution, the assignment plans of different scenario for FMOAP are reported in below tables for different values of the shape parameters and different estimates of aspiration levels specified by the DM. For each combination of the shape parameters, we presented results based on following different estimates of the aspiration levels.

1. Case-1: (K_1, K_2, K_3) = (-5, -1, -2); $\left(\overline{\mu}_{Z_1}(x), \overline{\mu}_{Z_2}(x), \overline{\mu}_{Z_3}(x)\right)$ = (0.7, 0.8, 0.9)
2. Case-2: (K_1, K_2, K_3) = (-5, -1, -2); $\left(\overline{\mu}_{Z_1}(x), \overline{\mu}_{Z_2}(x), \overline{\mu}_{Z_3}(x)\right)$ = (0.8, 0.85, 0.7)

3. Case-3: $(K_1,\ K_2,\ K_3)$ = (-5, -1, -2); $\left(\overline{\mu}_{Z_1}(x), \overline{\mu}_{Z_2}(x), \overline{\mu}_{Z_3}(x)\right)$ = (0.9, 0.7, 0.8)
4. Case-4: $(K_1,\ K_2,\ K_3)$ = (-1, -2, -5); $\left(\overline{\mu}_{Z_1}(x), \overline{\mu}_{Z_2}(x), \overline{\mu}_{Z_3}(x)\right)$ = (0.7, 0.85, 0.8)
5. Case-5: $(K_1,\ K_2,\ K_3)$ = (-1, -2, -5); $\left(\overline{\mu}_{Z_1}(x), \overline{\mu}_{Z_2}(x), \overline{\mu}_{Z_3}(x)\right)$ = (0.8, 0.75, 0.7)
6. Case-6: $(K_1,\ K_2,\ K_3)$ = (-2, -5, -1); $\left(\overline{\mu}_{Z_1}(x), \overline{\mu}_{Z_2}(x), \overline{\mu}_{Z_3}(x)\right)$ = (0.8, 0.85, 0.7)
7. Case-7: $(K_1,\ K_2,\ K_3)$ = (-2, -5, -1); $\left(\overline{\mu}_{Z_1}(x), \overline{\mu}_{Z_2}(x), \overline{\mu}_{Z_3}(x)\right)$ = (0.9, 0.75, 0.8)

Table 3. Summary results of different scenario for each objective at $\alpha = 0.1$

Case	Degree of satisfaction	Membership values $(\mu_{Z_{1j}},\ \mu_{Z_{2j}},\ \mu_{Z_{3j}})$	Objective values $(Z_1,\ Z_2,\ Z_3)$	Optimum allocations:
Optimistic scenario for each objective				
1	0.8377	(0.9584, 0.8377, 0.9869)	(27.9, 35.2, 5)	$x_{13}, x_{14}, x_{21}, x_{46}, x_{55}, x_{62}$
2	0.8844	(0.9241, 0.8844, 0.9436)	(31.2, 31.2, 8.1)	$x_{11}, x_{34}, x_{46}, x_{55}, x_{62}, x_{63}$
3	0.9111	(0.9111, 0.9185, 0.9601)	(31.2, 28.1, 7)	$x_{11}, x_{14}, x_{46}, x_{55}, x_{62}, x_{63}$
4	0.8025	(0.8025, 0.8825, 0.9763)	(24.8, 37.3, 12.1)	$x_{13}, x_{36}, x_{44}, x_{51}, x_{55}, x_{62}$
5	0.8025	(0.8025, 0.8825, 0.9763)	(24.8, 37.3, 12.1)	$x_{13}, x_{36}, x_{44}, x_{51}, x_{55}, x_{62}$
6	0.9115	(0.9115, 0.9450, 0.9300)	(22.7, 47.3, 7)	$x_{13}, x_{14}, x_{35}, x_{46}, x_{51}, x_{62}$
7	0.9032	(0.9254, 0.9274, 0.9032)	(21.8, 50.4, 8.1)	$x_{13}, x_{34}, x_{35}, x_{46}, x_{51}, x_{62}$
Most-likely scenario for each objective				
1	0.8691	(0.9640, 0.8691, 0.9777)	(37, 43, 14)	$x_{11}, x_{14}, x_{23}, x_{46}, x_{55}, x_{62}$
2	0.8691	(0.9343, 0.8691, 1)	(41, 43, 12)	$x_{13}, x_{14}, x_{31}, x_{46}, x_{55}, x_{62}$
3	0.8691	(0.9343, 0.8691, 1)	(41, 43, 12)	$x_{13}, x_{14}, x_{31}, x_{46}, x_{55}, x_{62}$
4	0.8427	(0.8636, 0.8427, 0.9883)	(31, 53, 18)	$x_{13}, x_{24}, x_{46}, x_{51}, x_{55}, x_{62}$
5	0.8636	(0.8636, 0.8688, 0.9709)	(31, 50, 22)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
6	0.9170	(0.9419, 0.9471, 0.9170)	(29, 59, 16)	$x_{13}, x_{14}, x_{35}, x_{46}, x_{51}, x_{62}$
7	0.8711	(0.9303, 0.9513, 0.8711)	(30, 58, 18)	$x_{14}, x_{23}, x_{35}, x_{46}, x_{51}, x_{62}$
Pessimistic scenario for each objective				
1	0.8611	(0.9070, 0.8611, 1)	(56.3, 57.4, 22.8)	$x_{13}, x_{14}, x_{31}, x_{46}, x_{55}, x_{62}$
2	0.8954	(0.8954, 0.9136, 0.9505)	(57.3, 51.5, 26.8)	$x_{11}, x_{14}, x_{46}, x_{55}, x_{62}, x_{63}$
3	0.8611	(0.9070, 0.8611, 1)	(56.3, 57.4, 22.8)	$x_{13}, x_{14}, x_{31}, x_{46}, x_{55}, x_{62}$
4	0.8135	(0.8749, 0.8135, 0.9535)	(40.8, 71.3, 34.8)	$x_{11}, x_{24}, x_{35}, x_{46}, x_{53}, x_{62}$
5	0.8135	(0.8765, 0.8135, 0.9800)	(40.7, 71.3, 30.8)	$x_{14}, x_{23}, x_{35}, x_{46}, x_{61}, x_{62}$
6	0.8667	(0.9161, 0.9452, 0.8667)	(41.7, 75.1, 28.8)	$x_{14}, x_{23}, x_{35}, x_{46}, x_{51}, x_{62}$
7	0.8667	(0.9052, 0.9582, 0.8667)	(42.7, 71.4, 28.8)	$x_{11}, x_{13}, x_{24}, x_{35}, x_{56}, x_{62}$

The Tables-3, 4 and 5 shows the summary of assignment plans for each objective at different values of confidence level for different scenario. It also show that change in confidence level influence spreads of the objective function i.e. as confidence level is increases, the influence of uncertainty in the fuzzy preference of the DM decreases.

Fig. 3 shows that the variations in the degree of satisfaction of cost, time and quality objectives corresponding to (-5, -1, -2) shape parameter at optimistic, most-likely and pessimistic scenario for $\alpha = 0.1$.

Table 4. Summary results of different scenario for each objective at $\alpha = 0.5$

Case	Degree of satisfaction	Membership values $(\mu_{Z_{1j}}, \mu_{Z_{2j}}, \mu_{Z_{3j}})$	Objective values (Z_1, Z_2, Z_3)	Optimum allocations:
Optimistic scenario for each objective				
1	0.8766	(0.9110, 0.8766, 0.9826)	(37, 36.5, 9)	$x_{14}, x_{23}, x_{31}, x_{46}, x_{55}, x_{62}$
2	0.8980	(0.9178, 0.8980, 0.9342)	(36.5, 34.5, 12.5)	$x_{14}, x_{21}, x_{46}, x_{55}, x_{62}, x_{63}$
3	0.8820	(0.9354, 0.8820, 0.9826)	(35, 36, 9)	$x_{11}, x_{14}, x_{23}, x_{45}, x_{46}, x_{52}$
4	0.8456	(0.8456, 0.8713, 0.9739)	(27, 43.5, 16.5)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
5	0.8456	(0.8456, 0.8713, 0.9739)	(27, 43.5, 16.5)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
6	0.9059	(0.9059, 0.9586, 0.9240)	(27, 49.5, 11)	$x_{13}, x_{14}, x_{21}, x_{35}, x_{46}, x_{62}$
7	0.8884	(0.9203, 0.9386, 0.8884)	(26, 54, 12.5)	$x_{13}, x_{24}, x_{46}, x_{55}, x_{61}, x_{62}$
Most-likely scenario for each objective				
1	0.8691	(0.9343, 0.8691, 1)	(41, 43, 12)	$x_{13}, x_{14}, x_{31}, x_{46}, x_{55}, x_{62}$
2	0.9189	(0.9241, 0.9189, 0.9522)	(42, 38, 16)	$x_{11}, x_{14}, x_{46}, x_{55}, x_{62}, x_{63}$
3	0.8994	(0.9343, 0.8994, 0.9522)	(41, 40, 16)	$x_{13}, x_{14}, x_{31}, x_{36}, x_{55}, x_{62}$
4	0.8636	(0.8636, 0.8688, 0.9709)	(31, 50, 22)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
5	0.8636	(0.8636, 0.8688, 0.9709)	(31, 50, 22)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
6	0.8916	(0.8916, 0.9588, 0.9170)	(33, 56, 16)	$x_{13}, x_{15}, x_{24}, x_{46}, x_{51}, x_{62}$
7	0.8711	(0.9052, 0.9709, 0.8711)	(32, 52, 18)	$x_{11}, x_{13}, x_{35}, x_{44}, x_{56}, x_{62}$
Pessimistic scenario for each objective				
1	0.9080	(0.9080, 0.9158, 0.9512)	(50.5, 45.5, 22)	$x_{11}, x_{14}, x_{46}, x_{55}, x_{62}, x_{63}$
2	0.9080	(0.9080, 0.9158, 0.9512)	(50.5, 45.5, 22)	$x_{11}, x_{14}, x_{46}, x_{55}, x_{62}, x_{63}$
3	0.8245	(0.9638, 0.8245, 0.9773)	(43.5, 55, 20)	$x_{13}, x_{14}, x_{21}, x_{46}, x_{55}, x_{62}$
4	0.8167	(0.8167, 0.8690, 0.9698)	(39.5, 58, 28)	$x_{13}, x_{36}, x_{44}, x_{51}, x_{55}, x_{62}$
5	0.8405	(0.8779, 0.8405, 0.9549)	(36, 61.5, 30)	$x_{11}, x_{23}, x_{35}, x_{36}, x_{44}, x_{62}$
6	0.8687	(0.9219, 0.9478, 0.8687)	(36.5, 67.5, 24)	$x_{14}, x_{23}, x_{35}, x_{46}, x_{51}, x_{62}$
7	0.8687	(0.9219, 0.9478, 0.8687)	(36.5, 67.5, 24)	$x_{14}, x_{23}, x_{35}, x_{46}, x_{51}, x_{62}$

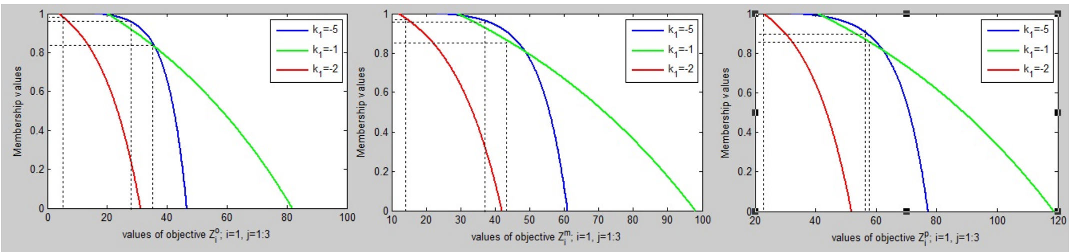

Fig. 3. The degree of satisfaction level of each objective at three different scenarios for with (-5, -1, -2) shape parameter and (0.7, 0.8, 0.9) Aspiration level

Figs. 4, 5 and 6 shows the variation in the degree of satisfaction of the goal of cost, time and quality objectives corresponding to a different choice of shape parameter at optimistic, most-likely and pessimistic scenario for different values ofα. From the above figures, we also show the advantage of the using the exponential membership function with different shape parameter in FMOAP. If DM is not satisfied with obtaining assignment plans more plans can be generated by changing the values of confidence level and values of shape parameters [13].

Table 5. Summary results of different scenario for each objective at $\alpha = 0.9$

Case	Degree of satisfaction	Membership values $(\mu_{Z_{1j}}, \mu_{Z_{2j}}, \mu_{Z_{3j}})$	Objective values (Z_1, Z_2, Z_3)	Optimum allocations:
Optimistic scenario for each objective				
1	0.8684	(0.9326, 0.8684, 1)	(40, 41.9, 11.1)	$x_{11}, x_{14}, x_{46}, x_{55}, x_{62}, x_{63}$
2	0.9189	(0.9230, 0.9189, 0.9530)	(40.9, 36.9, 15)	$x_{13}, x_{14}, x_{31}, x_{55}, x_{56}, x_{62}$
3	0.8483	(0.9628, 0.8483, 0.9544)	(36.1, 43.8, 14.9)	$x_{14}, x_{21}, x_{23}, x_{46}, x_{55}, x_{62}$
4	0.7806	(0.7806, 0.9226, 0.9715)	(34.1, 41.7, 20.9)	$x_{11}, x_{23}, x_{36}, x_{44}, x_{55}, x_{62}$
5	0.8604	(0.8604, 0.8693, 0.9715)	(30.2, 48.7, 20.9)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
6	0.8405	(0.8405, 0.9801, 0.9616)	(35, 46.7, 13)	$x_{11}, x_{13}, x_{34}, x_{46}, x_{55}, x_{62}$
7	0.8745	(0.9026, 0.9710, 0.8745)	(31.2, 50.7, 16.9)	$x_{13}, x_{34}, x_{35}, x_{46}, x_{51}, x_{62}$
Most-likely scenario for each objective				
1	0.8793	(0.9241, 0.8793, 0.9777)	(42, 42, 14)	$x_{14}, x_{23}, x_{31}, x_{46}, x_{55}, x_{63}$
2	0.8691	(0.9640, 0.8691, 0.9777)	(37, 43, 14)	$x_{11}, x_{14}, x_{23}, x_{46}, x_{55}, x_{62}$
3	0.8793	(0.9241, 0.8793, 0.9777)	(42, 42, 14)	$x_{14}, x_{23}, x_{31}, x_{46}, x_{55}, x_{63}$
4	0.8636	(0.8636, 0.8688, 0.9709)	(31, 50, 22)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
5	0.8046	(0.8046, 0.9148, 0.9801)	(34, 44, 20)	$x_{11}, x_{13}, x_{36}, x_{44}, x_{55}, x_{62}$
6	0.9170	(0.9419, 0.9471, 0.9170)	(29, 59, 16)	$x_{13}, x_{14}, x_{35}, x_{46}, x_{51}, x_{62}$
7	0.9003	(0.9529, 0.9003, 0.9170)	(28, 67, 16)	$x_{13}, x_{14}, x_{35}, x_{46}, x_{61}, x_{62}$
Pessimistic scenario for each objective				
1	0.8671	(0.9623, 0.8671, 0.9776)	(38.6, 44.7, 15.2)	$x_{11}, x_{14}, x_{23}, x_{46}, x_{55}, x_{62}$
2	0.8681	(0.9313, 0.8681, 1)	(42.7, 44.6, 13.2)	$x_{13}, x_{14}, x_{31}, x_{46}, x_{55}, x_{62}$
3	0.9183	(0.9209, 0.9183, 0.9520)	(43.7, 39.5, 17.2)	$x_{11}, x_{14}, x_{46}, x_{55}, x_{62}, x_{63}$
4	0.8575	(0.8575, 0.8672, 0.9707)	(32.5, 51.8, 23.2)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
5	0.8575	(0.8575, 0.8672, 0.9707)	(32.5, 51.8, 23.2)	$x_{13}, x_{24}, x_{36}, x_{51}, x_{55}, x_{62}$
6	0.8719	(0.8719, 0.9774, 0.9597)	(35.6, 50.8, 15.2)	$x_{13}, x_{14}, x_{46}, x_{51}, x_{55}, x_{62}$
7	0.8707	(0.9011, 0.9702, 0.8707)	(33.5, 53.9, 19.2)	$x_{13}, x_{44}, x_{46}, x_{51}, x_{55}, x_{62}$

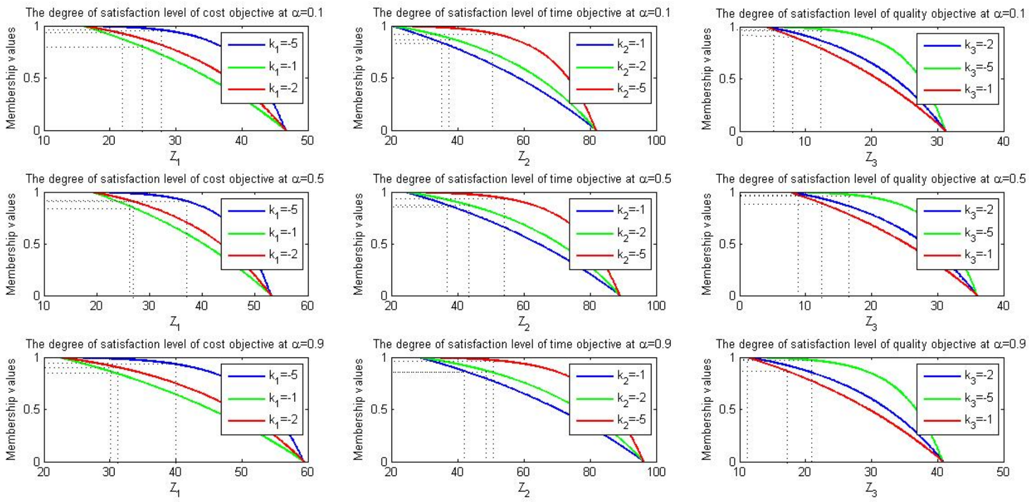

Fig. 4. The degree of satisfaction of optimistic case of each objective at and

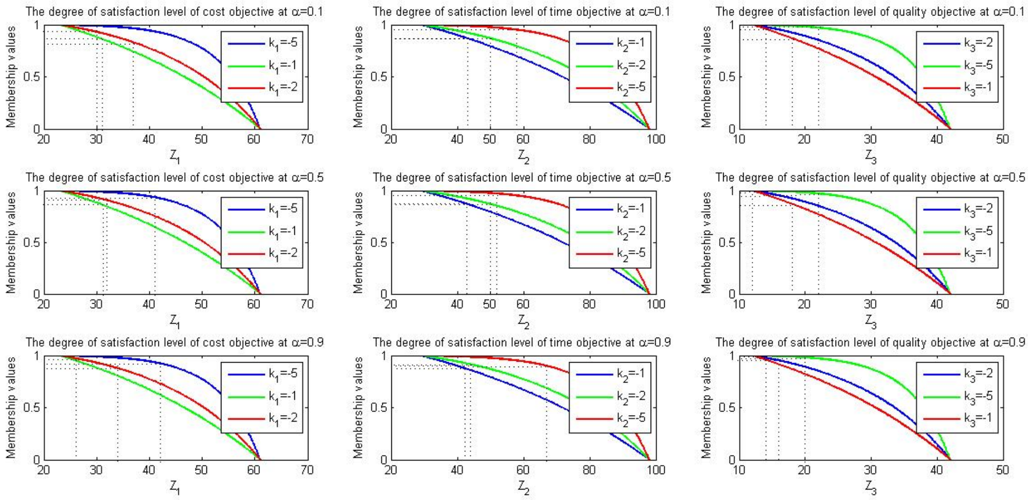

Fig. 5. The degree of satisfaction of most likely case of each objective at and

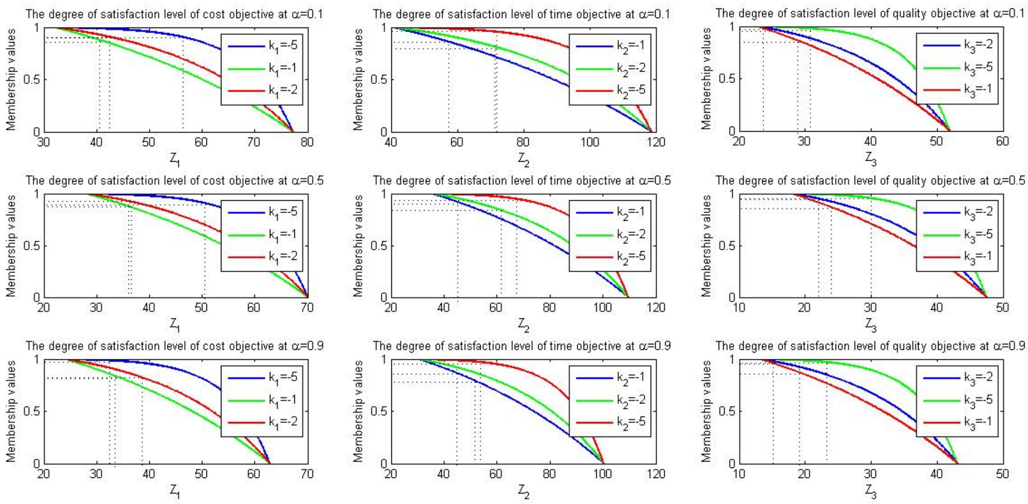

Fig. 6. The degree of satisfaction of pessimistic case of each objective at and

The genetic algorithm based hybrid approach gives flexibility and large collection of information in sense of changing the α level as well as changing the shape parameters in exponential membership function and also provides the different scenario analysis to DM for fuzzy allocation strategy. This approach also treated three objectives consistently. For example, cost, time and quality objective assignment problem, DM gives the priority to the cost objective in determining the period of allocation plan; the solution is chosen by DM which satisfies the cost objective function most than others. However, it can be causes by poor performance of the degree of satisfaction level of one objective may be compensated by the good performance of others. Hence, the DM can choose different solution in different situation, according his \her help ([12],[13]).

6 Conclusion

Genetic algorithm based hybrid approach provided the solution of optimistic, most likely and pessimistic scenarios of fuzzy multi-objective assignment problem using exponential membership function with subject to some realistic constraints with triangular possibilistic distribution. The developed hybrid approach provided flexibility in a different situation for the DM and also provided better assignment plans as per the scenario.

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Competing Interests

Authors have declared that no competing interests exist.

References

[1] Pentico David W. Assignment problems: A golden anniversary survey. European Journal of Operational Research. 2007;176(2):774-793.

[2] Zadeh LA. Fuzzy sets, Inform. Contr. 1965;8(3):338-353.

[3] Tsai CH, Wei CC and Cheng CL. Multi-objective fuzzy deployment of manpow multi-objective fuzzy deployment of manpower. Inter. J. Comp. Int. Manag. 1999;7(2):1-9.

[4] Lin CJ, Wen UP. A labeling algorithm for the fuzzy assignment problem. Fuzzy Sets Syst. 2004;142(3):373-391.

[5] Lin CJ, Wen UP, Lin PY. Advanced sensitivity analysis of the fuzzy assignment problem. Appl. Soft Comput. 2011;11(8):5341-5349.

[6] Li F, Xub LD, Jin C, Wang H. Study on solution models and methods for the fuzzy assignment problems. Expert Syst. Appl. 2012;39(12):11276-11283.

[7] Kagade KL, Bajaj VH. Fuzzy method for solving multi-objective assignment problem with interval cost. J. Stat. Math. 2010;1(1):1-9.

[8] Kagade KL, Bajaj VH. Fuzzy approach with linear and some non-linear membership functions for solving multi-objective assignment problems. J Adv Comput Res. 2009;1:14-17.

[9] Kumar A, Gupta A. Methods for solving fuzzy assignment problems and fuzzy travelling salesman problems with different membership functions. Fuzzy Inf. Eng. 2011;3(1):3-21.

[10] Liu Linzhong, Xin Gao. Fuzzy weighted equilibrium multi-job assignment problem and genetic algorithm. Applied Mathematical Modelling. 2009;33(10):3926-3935.

[11] De PK, Yadav B. An algorithm to solve multi-objective assignment problem using interactive fuzzy goal programming approach. Int. J. Contemp. Math. Sciences. 2011;6(33-36):1651-1662.

[12] Pankaj Gupta, Mukesh Kumar Mehlawat. A fuzzy approach to multi-criteria assignment problem using exponential membership functions. Int. J. Mach. Learn. and Cyber. 2013;4:647-657.

[13] Pankaj Gupta, Mukesh Kumar Mehlawat. A new possibilistic programming approach for solving fuzzy multi-objective assignment problem. Ieee Transactions on Fuzzy Systems. 2014;21(1):16-34. ISSN: 1063-6706

[14] Mukherjee S, Basu K. Application of fuzzy ranking method for solving assignment problems with fuzzy costs. Int. J. Comput. Appl. Math. 2010;5(3):359-368.

[15] Feng Y, Yang L. A two-objective fuzzy k-cardinality assignment problem. J. Comput. Appl. Math. 2006;197(1):233-244.

[16] Harish Garg. Multi-objective optimization problem of system reliability under intuitionistic fuzzy set environment using Cuckoo search algorithm. Journal of Intelligent and Fuzzy Systems, IOS Press. 2015;29(4):1653-1669.

[17] Harish Garg. A new generalized improved score function of interval-valued intuitionistic fuzzy sets and application in expert systems. Applied Soft Computing, Elsevier. 2016;38:988-999.

[18] Harish Garg, Monica Rani, Sharma SP, Yashi Vishwakarma. Bi-objective optimization of the reliability-redundancy allocation problem for series-parallel system. Journal of Manufacturing System, Elsevier. 2014;33(3):335-347.

[19] Harish Garg, Monica Rani, Sharma SP, Yashi Vishwakarma. Intuitionistic fuzzy optimization technique for solving multi-objective reliability optimization problems in interval environment. Expert Systems with Applications, Elsevier. 2014;41(7):3157-3167.

[20] Tanaka H, Ichihashi H, Asai K. Formulation of fuzzy linear programming problem based on comparison of fuzzy numbers. Contr.Cybern. 1984;13:185-194.

[21] Luhandjula MK. Linear programming with a possibilistic objective function. European Journal of Operational Research. 1987;31(1):110-117.

[22] Wang RC, Liang TF. Applying possibilistic linear programming to aggregate production planning. Int. J. Prod. Econ. 2005;98(3):328-341.

[23] Rommelfanger Heinrich, Randolf Hanuscheck, Jochen Wolf. Linear programming with fuzzy objectives. Fuzzy Sets and Systems.1989;29(1):31-48.

[24] Rommelfanger Heinrich. Interactive decision making in fuzzy linear optimization problems. European Journal of Operational Research. 1989;41(2):210-217.

[25] Lai YJ, Hwang CL. A new approach to some Possibilistic linear programming problems. Fuzzy Sets Syst., 1992;49(2):121-133.

[26] Ratli Mustapha, et al . Hybrid genetic algorithm for bi-objective assignment problem. Industrial Engineering and Systems Management (IESM). Proceedings of 2013 International Conference on. IEEE; 2013

[27] Anita Ravi Tailor, Jayesh M. Dhodiya. Genetic algorithm based hybrid approach to solve multi-objective assignment problem. International Journal of Innovative Research in Science, Engineering and Technology. 2016;5(1):524-535.

[28] Toroslu Ismail H, Yilmaz Arslanoglu. Genetic algorithm for the personnel assignment problem with multiple objectives. Information Sciences. 2007;177(3):787-803.

[29] Herrera F, Lpez E, Mendana C, Rodrıguez MA. Solving an assignment–selection problem with verbal information and using genetic algorithms. European Journal of Operational Research. 1999;119(2):326-337.

[30] Huang Gaofeng, Andrew Lim. A hybrid genetic algorithm for the three-index assignment problem. European Journal of Operational Research. 2006;172(1):249-257.

[31] Sahu Anshuman, Rudrajit Tapadar. Solving the assignment problem using genetic algorithm and simulated annealing. In IMECS. 2006:762-765.

[32] Harper PR, de Senna V, Vieira IT, Shahani AK. A genetic algorithm for the project assignment problem. Computers & Operations Research. 2005;32(5):1255-1265.

[33] Oh Y, Hwang H, Cha CN, Lee S. A dock-door assignment problem for the Korean mail distribution center. Computers & Industrial Engineering. 2006;51(2):288-296.

[34] Harish Garg. A hybrid PSO-GA algorithm for constrained optimization problems. Applied Mathematics and Computation, Elsevier. 2016;274:292-305.

[35] Hannan EL. Linear programming with multiple fuzzy goals. Fuzzy Sets Syst.1981;6(3):235-248.

[36] Hsu HM, Wang WP. Possibilistic programming in production planning of assemble-to-order environments. Fuzzy Sets Syst. 2001;119(1):59-70.

[37] Buckley JJ. Possibilistic linear programming with triangular fuzzy numbers. Fuzzy Sets Syst. 1988;26(1):135-138.

[38] Sivanandam SN, Deepa SN. Introduction to genetic algorithms. Springer Science & Business Media; 2007.

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