Journal of Engineering and Applied Sciences 11 (1): 112-118, 2016
ISSN: 1816-949X

Optimization of Fuzzy Multi-Criteria Transportation Problems: A Case of Specific Hybrid Evolutionary Algorithm

[1]Mohammad Mohammadi Najafabadi and [2]Sara Mansouri
[1]Department of Computer Science, Payame Noor University (PNU), P.O. Box 19395-3697, Tehran, Iran
[2]Department of Teaching English Language, Faculty of Humanities, Najafabad Branch, Islamic Azad University, Najafabad, Isfahan, Iran

Abstract: The problem of transportation is one of the most frequently problems considered in the field of research in operations. In previous studies, by considering issues such as different transportation vehicles, the number of goods and different objective functions, it was tried to make the model more realistic. In this study, in addition to considering these items in the proposed model, the uncertainty in the model is considered and for this purpose, fuzzy theory is used. In the proposed model, in addition to parameters, decision variables are defined as triangular fuzzy numbers.

Key words: Transportation problem, fuzzy linear programming, hybrid evolutionary algorithms, fuzzy optimization, functions

INTRODUCTION

Transportation problems with multi-criteria approach in addition to transportation costs review other limitations such as goods delivery time, the extent of goods delivery, reliability of the reduced transport capacity, access to transport users and the deterioration of production that can be taken into account while designing transport model. To design a mathematical model, a real-world modern system, given the complexity of these systems both socially and economically and moreover unpredictable factors such as weather problems have posed a lot of problems to investigators in determining appropriate values of the model parameters. One of the methods that enable to create and design of such systems is fuzzy programming with uncertainty in decision-making. To address this issue, the following multi-criteria fuzzy transportation problem is considered. Suppose that in general, transport problem has m origin or source and n destination that with k methods or routes goods are sent from origin to destination and also the production of goods at ith source is equal to a_i and the amount of demand for the goods at jth destination is equal to b_j and e_k is the amount of goods that can be transferred using kth path (Abd El-Wahed, 2001):

$$\min \tilde{z}_q = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p}\tilde{c}_{ijk}^{q} x_{ijk} \quad q = 1, 2, ..., Q \tag{1}$$

$$\text{s.t.} \sum_{j=1}^{n}\sum_{k=1}^{p} x_{ijk} = a_i \quad i = 1, 2, ..., m \tag{2}$$

$$\sum_{i=1}^{m}\sum_{k=1}^{p} x_{ijk} = b_j \quad j = 1, 2, ..., n \tag{3}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ijk} = e_k \quad k = 1, 2, ..., p \tag{4}$$

$$x_{ijk} \geq 0 \quad \forall\, i, j, k$$

So that for every i, j, k, there is $a_i \geq 0$, $b_j \geq 0$, $e_k \geq 0$. The limitations of this problem are the same as common limitations of transport problems and the only difference is the coefficients of the objective function all of which are identified as $\tilde{c}_{ijk}^{q}$ fuzzy numbers for q = 1, 2, …., Q (Chern *et al*., 2010).

INTRODUCTION OF HYBRID EVOLUTIONARY ALGORITHMS

Hybrid evolutionary algorithms are defined as branch of social optimization techniques where biological systems and the principles ruling them are used. Although, these algorithms provide simple models of biological processes in normal circumstances, they have shown a lot of ability and efficiency in practice. The

Corresponding Author: Mohammad Mohammadi Najafabadi, Department of Computer Science, Payame Noor University (PNU), P.O. Box 19395-3697, Tehran, Iran

basic idea of offering evolutionary algorithms is using a limited population of elements, each of which determines a point of search space where the algorithm of the population is defined by chromosomes. After this stage, chromosomes populations (people of the society) enter the evolutionary process slope in nature. At first, a population of chromosomes is created randomly and then recombination, mutation choice and other operators of evolution depending on the need are applied on this chromosome to get a new generation of chromosomes and then optimization criteria for the new generation are checked. If optimality criteria are met for this new generation, the algorithm is stopped and the best chromosome of the generation is selected as the optimum solution and transport model is achieved. Otherwise, genetic operators are applied on chromosomes within the population and new generation is created and these stages continue until meeting the optimality criteria (Dubois *et al*., 2003). Hybrid evolutionary algorithms superiority to other methods of optimization causes them to be popular. From the beginning of the creation of evolutionary algorithms, the experts have tried to make these algorithms simpler and more understandable and tried to offer other models of evolutionary algorithms with fewer operations and many capabilities in different fields of optimization with outputs of these algorithms providing the best answer to the problem.

EVOLUTIONARY ALGORITHM SOLUTION

In this study, a special hybrid evolutionary algorithm approach is suggested to solve the problem of multi-criteria fuzzy transportation. In multi-criteria optimization method, researchers are interested in finding Pareto solutions (Chern *et al*., 2010). When in multi-criteria optimization problems the coefficients of the objective function is in the form of fuzzy numbers, so the objective function value will be obtained as a fuzzy number. Thus, comparing these numbers is not as simple as comparing integers and for determining which solution is a Pareto solution, fuzzy techniques should be used. In this research, fuzzy rating techniques can help us to compare fuzzy numbers. So, the fuzzy ranking used in this study should be stated firstly.

Ranking fuzzy numbers using their integral value: In the present, a ranking method based on integral values has been proposed described in this section. Suppose that $\mu_{\tilde{A}(x)}$ is a membership function for triangular fuzzy number Ã which stated as (a_1, a_2, a_3) and its graph is given in Fig. 1, so as you can see, a membership function can be divided into two parts: the right and left side.

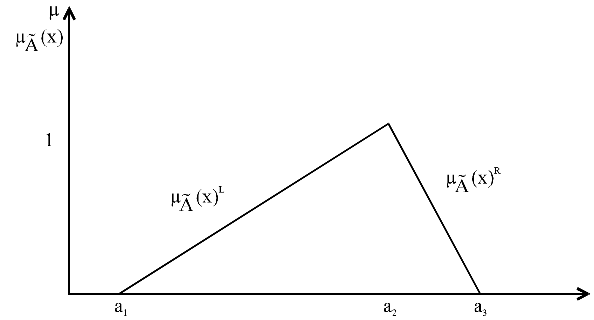

Fig. 1: The membership function

For minimization problems, integral value of the inverse function of the left side of the membership function of the fuzzy number Ã expresses the optimistic view and reflects the inverse function on the right part. Pessimistic view is from the decision maker. A convex combination of inverse function integral values of the left and right side of the membership function is called the general integral which is used to rank fuzzy numbers (Cadenas and Verdegay, 1997). Suppose that Ã is a triangular fuzzy number defined as (a_1, a_2, a_3), then, its membership function is as follows:

$$\mu_{\tilde{A}}(x)=\begin{cases}\dfrac{(x-a_1)}{(a_2-a_1)} & a_1\le x\le a_2\\ \dfrac{(x-a_3)}{(a_2-a_3)} & a_2\le x\le a_3\\ 0 & \text{otherwise}\end{cases} \tag{5}$$

where (a_1, a_2, a_3) are all integers. Now, based on this fuzzy number, right membership function $\mu_{\tilde{A}}(x)^R$ and left membership function $\mu_{\tilde{A}}(x)^L$ are defined as following:

$$\mu_{\tilde{A}}(x)^L=\frac{(x-a_1)}{(a_2-a_1)} \tag{6}$$

$$\mu_{\tilde{A}}(x)^R=\frac{(x-a_3)}{(a_2-a_3)} \tag{7}$$

And its inverse functions can be obtained as follows:

$$g_{\tilde{A}}(y)^L=a_1+(a_2-a_1)y \tag{8}$$

$$g_{\tilde{A}}(y)^R=a_3+(a_2-a_3)y \tag{9}$$

According to inverse functions, now, left and right integrals can be calculated:

$$I(\tilde{A})^L = \int_0^1 g_{\tilde{A}}(y)^L dy = \frac{1}{2}(a_1 + a_2) \quad (10)$$

$$I(\tilde{A})^R = \int_0^1 g_{\tilde{A}}(y)^R dy = \frac{1}{2}(a_2 + a_3) \quad (11)$$

Therefore, the integral of total fuzzy number $\tilde{A}$ is obtained as follows:

$$I^a(\tilde{A}) = aI(\tilde{A})^R + (1\text{-}a)I(\tilde{A})^L = \frac{1}{2}[aa_3 + a_2 + (1\text{-}a)a_1] \quad (12)$$

And for to adjust in the efficiency of decision-makers, $a \in [0, 1]$ is considered. Here, although optimal decision degree (a) is equal to 0.5, total integral represents the average value. For example, the value of total integral for two triangle fuzzy numbers $\tilde{A}_1 = (3, 4, 7)$, $\tilde{A}_2 = (4, 5, 51/8)$ is equal to:

$$I^a(\tilde{A}_1) = 4 + 2a$$

$$I^a(\tilde{A}_2) = 4.5 + 1.2a$$

In minimization problems, the pessimistic mode for a decision maker is when a = 1 resulting in $\tilde{A}_1 > \tilde{A}_2$ and the optimistic mode is when a = 0 and we have $\tilde{A}_1 < \tilde{A}_2$ and the moderate mode is a = 0.5 when we have $\tilde{A}_1 > \tilde{A}_2$.

Using this ranking method, fuzzy objective function values can be made into integral values and Pareto solution can be determined based on the integral values (Jimenez *et al*., 2007).

Evaluation of chromosomes in Hybrid Evolutionary algorithm: The quality of determining the merit and evaluation of each multi-criteria chromosome is relatively a complex job in the stages of development of hybrid evolutionary algorithms. In this study, summing up method is used for calculating the fitness values of chromosomes which is applicable as follows (Fogel, 1994).

Evaluation method:

- Step one: calculating the fuzzy objective function values $\tilde{z}_q(X_s)$, q = 1, 2, ..., Q and for each chromosome X_s, s = 1, 2, ..., pop-size
- Step two: converting fuzzy numbers $\tilde{z}_q(X_s)$ to integral values $I_q^a(\tilde{z}_q(X_s))$ through ranking method
- Step three: determining the minimum and maximum integral value for each objective function as follows (Chen and Chang, 2006)

$$I_q^{min} = \min\{I_q^a \tilde{z}_q(X_s)\ s = 1, 2, ..., pop_{size}\}, \quad q = 1, 2, ..., Q$$

$$I_q^{max} = \max\{I_q^a \tilde{z}_q(X_s)\ s = 1, 2, ..., pop_{size}\}, \quad q = 1, 2, ..., Q$$

- Step four: calculating weight coefficients as follows

$$\delta_q = I_q^{max} - I_q^{min}, \quad q = 1, 2, ..., Q$$

$$\beta_q = \frac{\delta_q}{\sum_{q=1}^{Q} \delta_q} \quad q = 1, 2, ..., Q$$

- Step five: calculating fitness values for each chromosome by using the following equation

$$eval(X_s) = \sum_{q=1}^{Q} \beta_q I_q^a(\tilde{z}_q(X_s)), \quad s = 1, 2, ..., pop_{size}$$

Recombination: Suppose the probability of recombination of chromosomes from one generation is $p_c = 0.3$, this means that 20% of the entire chromosome for each generation undergoes a recombination (Vignaux and Michalewicx, 1991). However, because the chromosomes genes are regarded as integers, so non-even recombination operator is used. First, a series of structural chromosomal genes in accordance with values of zero and one as the length of chromosomes is randomly generated and this thread is used as a model for recombination. Suppose that the following pattern is created randomly and the following two chromosomes are chosen as first and second parents. Now, the first and second children are created according to the pattern of the first and second parent, so that the genes of the parents' genes are moved when the gene like them in the model is as one and otherwise movement does not take place in the parents. Now suppose that the first and second parents are obtained from a generation as follows. We know these two parents go for all limitations of the problem.

A new operator introduced here is the result of combining operator of the wheel selection as well as chromosome ranking technique (Vasant, 2005). In this operator, a rank is given to each chromosomes of the first generation firstly where ranking process is against common ranking, so that the worst chromosome is the first and the best is the last chromosome. Based on the following formula, the fitness related to the chromosomes of a given generation is obtained where sp is a random number between Eq. 1 and 2 and pos is the rank of the chromosome in the generation (Fig. 2):

First parent

3	5	0	1	2	4	3	3	4
4	4	1	2	2	2	1	1	3
3	1	1	3	1	1	0	1	5

Second parent

0	4	4	6	1	0	5	0	5
6	3	0	3	2	1	4	1	0
0	3	2	4	0	1	3	3	0

Model

1	0	0	1	1	0	1	0	0
1	1	0	0	0	0	1	1	0
0	1	1	0	0	1	0	1	0

First child

0	5	0	6	1	4	5	3	4
6	3	1	2	2	2	4	1	3
3	3	2	3	1	1	0	3	5

Second child

3	4	4	1	2	0	3	0	5
4	4	0	3	2	1	1	1	0
0	1	1	4	0	1	3	1	0

Fig. 2: Evaluation of chromosomes in Hybrid Evolutionary algorithm

$$\text{Fittness(pos)} = 2\text{-sp} + 2\times(\text{sp-1})\times\frac{(\text{pos-1})}{(\text{N-1})}$$

Now, suppose that the number of chromosomes of our first generation is equal to n, then rank of the worst answer is one and the same way the rank of the best answer is n and according to the above formula, its fitness level is obtained such as $f_1, f_2, ..., f_n$ and now, it acts based on the following. At first the amount of:

$$F = \sum_{i=1}^{n} f_i$$

is obtained, then the probability of choosing each answer is given as follows:

$$P_i = \frac{f_i}{F}$$

Accordingly, cumulative probability of each of the solutions is calculated as follows:

$$q_1 = p_1,\ q_i = q_{i-1} + p_i,\ i = 2, 3, ..., n$$

Then, they are pictured on a Vera on a segment from zero to one. Now, the same as number of options that need to be done, random numbers are selected in the interval [0, 1], the answers similar to these numbers are selected. Obviously, stronger answers have greater fitness and they are more likely to be chosen compared to other solutions of a generation and this is based on Darwin's principle of natural selection that strong animals remain and the weak are doomed to die out. Suppose that by the operator of transport model selection n number of new chromosomes is chosen as a great number of its solutions may be repetitive. Now, after applying the selection operator, recombination operator affects the solutions of this generation so that new chromosomes are achieved (Karabuk, 2007).

THE IMPLEMENTATION STAGES OF THE ALGORITHM

Now firstly, based on the feasible area, we randomly generate the problem of zero or first generation and obtain its fitness, then assess the optimality criteria for this generation. If the criteria of optimality algorithm are met, algorithm stages are stopped and the best chromosome of that generation is selected as the solution to the problem. Otherwise, selection operator is applied on this generation of chromosomes and n new chromosomes are selected. After this step, the chromosomal recombination operator is applied on this generation an n chromosome is replicated to 2n chromosome which makes diversity in the chromosomes. After this step, the mutation operator is applied, so that n chromosome is converted to n new chromosome, according to the process that the operator has mutation. So after these stages, 4n new chromosome is achieved. Now as the number of a cell must remain stable, selection operator is used n number of chromosomes is chosen from 4n chromosome. Moreover, these n chromosomes form a new generation. Now as the process mentioned above, we check the optimality criteria for this generation. If optimality criteria are met, the best chromosome is selected; otherwise, evolutionary operators are applied on this generation and a new generation is obtained. This process will continue until the optimality criteria are met and algorithm is stopped and the best solution achieved. This algorithm is designed based on the specific characteristics of the transport model and has the ability to be used for other problems as well (Teodorovici, 2007). Ingeneral, algorithm can be designed step by step as the following:

- Step one: creating answers at random as the initial generation
- Step two: getting the value of the objective function to determine the fitness of this generation
- Step three: assessing the optimality criterion and if met go to step seven
- Step four: applying recombination operator
- Step five: applying mutation
- Step six: applying operator selection and going to the second step
- Seventh step: getting the optimum solution

BEST COMPROMISE SOLUTION

To determine the best compromise solution among Prato solutions, TOPSIS Method has been used in hybrid evolutionary algorithms. TOPSIS stands for the technique to rank order according to the ideal solution which is similar to the notion that alternative should be the shortest distance from the positive ideal solution (Haghani and Oh, 1996) and far from the ideal negative solution.

Suppose that X_k is the Prato solution in the last generation of the hybrid evolutionary algorithm. TOPSIS Method acts as follows.

TOPSIS Method:

- Step 1: determining positive and negative ideal relative solutions according to the following equation:

$$I_q^+ = \min\left\{I_q^a \tilde{z}_q(X_s)\ s = 1, 2, ..., m\right\}, \quad q = 1, 2, ..., Q$$

$$I_q^- = \max\left\{I_q^a \tilde{z}_q(X_s)\ s = 1, 2, ..., m\right\}, \quad q = 1, 2, ..., Q$$

- Step 2: normalizing the values according to the following directive:

$$r_q^k = \frac{I_q^a(\tilde{z}_q(X_k))}{\sqrt{\sum_{s=1}^{m} (I_q^a(\tilde{z}_q(X_s)))^2 + (I_q^+)^2 + (I_q^-)^2}}$$

- Step 3: calculating the separated weights

$$s_q^+ = \sqrt{\sum_{q=1}^{Q} w_q^2(r_q^+ - r_q^k)^2}, \quad k = 1, 2, ..., m$$

$$s_q^- = \sqrt{\sum_{q=1}^{Q} w_q^2(r_q^k - r_q^-)^2}, \quad k = 1, 2, ..., m$$

where, normalized r_q^+ and r_q^- is I_q^+ and I_q^- and W_q is equal to relative importance (weight) of the objective function that applies in the following condition:

$$\sum_{q=1}^{Q} w_q = 1, \quad w_q \in [0, 1]$$

- Step 4: calculating the relative closeness to the optimal solution:

$$d_k = \frac{s_k}{s_k^+ + s_k^-}, \ k = 1, 2, ..., m$$

- Step 5: rank in the order of priority: now Parto solutions can be ordered in a descending order (Yang and Feng, 2007). Now, according to what was said above, different steps of this algorithm can be offered as programmer code

Procedure: fuzzy multicriteria transportation problem:

```
begin
 t = 0;
initialize p(t);
evaluate p(t);
create Pareto solution E(t);
while (not termination condition) do
recombine p(t);
mutation P(t);
evaluate p(t);
select p(t);
update Pareto solution E(t);
t = t+1;
end;
determine the best compromise solution;
end
```

SUBJECT OF THE RESEARCH AND ITS RESULTS

To address this issue, we consider multi-criteria fuzzy transport problem (Amid *et al*., 2006). Suppose that transport problem has 3 (m = 3) origin or source as well 3 (n = 3) destination that is sends goods by 3 (k = 3) methods or routes from origin to destination and the production of goods at ith origin equal to α_i and the amount of demand for the goods at jth destination as b_j and e_k is the amount of goods can be transmitted by kth method or path all of which are identified in the following numerical problem and coefficients of objective function all of which are fuzzy (Abd El-Wahed, 2001) are shown in Table 1:

$$\min \tilde{z}_q = \sum_{i=1}^{3}\sum_{j=1}^{3}\sum_{k=1}^{3} \tilde{c}_{ijk}^q\ x_{ijk}, \quad q = 1, 2, 3$$

$$\text{s.t.} = \sum_{j=1}^{3}\sum_{k=1}^{3} x_{1jk} = 8,\ \sum_{j=1}^{3}\sum_{k=1}^{3} x_{2jk} = 9,\ \sum_{j=1}^{3}\sum_{k=1}^{3} x_{3jk} = 5$$

$$\sum_{i=1}^{3}\sum_{k=1}^{3} x_{i1k} = 7,\ \sum_{i=1}^{3}\sum_{k=1}^{3} x_{i2k} = 6,\ \sum_{i=1}^{3}\sum_{k=1}^{3} x_{i3k} = 5$$

Table 1: Fuzzy coefficients of the objective function

	1			2			3		
q (k)	1	1	3	1	2	3	1	2	3
$\tilde{c}^a_{11k}$	(8, 9, 10)	(8, 9, 10)	(7, 9, 11)	(3, 6, 9)	(8, 9, 10)	(5, 7, 9)	(2, 3, 4)	(6, 7, 8)	(5, 7, 9)
$\tilde{c}^a_{12k}$	(4, 5, 6)	(4, 5, 6)	(3, 5, 7)	(7, 9, 11)	(8, 11, 14)	(1, 3, 5)	(5, 6, 7)	(6, 8, 10)	(5, 6, 7)
$\tilde{c}^a_{13k}$	(1, 2, 3)	(1, 2, 3)	(1, 1, 1)	(1, 2, 3)	(6, 7, 8)	(6, 7, 8)	(1, 1, 1)	(8, 9, 10)	(1, 3, 5)
$\tilde{c}^a_{21k}$	(1, 2, 3)	(1, 2, 3)	(6, 8, 10)	(1, 1, 1)	(2, 4, 6)	(1, 1, 1)	(7, 9, 11)	(7, 9, 11)	(4, 5, 6)
$\tilde{c}^a_{22k}$	(1, 2, 3)	(1, 2, 3)	(1, 1, 1)	(3, 4, 5)	(3, 5, 7)	(1, 2, 3)	(6, 8, 10)	(5, 6, 7)	(8, 9, 10)
$\tilde{c}^a_{23k}$	(4, 5, 6)	(4, 5, 6)	(5, 7, 9)	(6, 8, 10)	(8, 9, 10)	(6, 7, 8)	(3, 5, 7)	(1, 2, 3)	(3, 5, 7)
$\tilde{c}^a_{31k}$	(1, 2, 3)	(1, 2, 3)	(5, 6, 7)	(2, 3, 4)	(4, 6, 8)	(3, 4, 5)	(6, 8, 10)	(2, 4, 6)	(7, 9, 11)
$\tilde{c}^a_{32k}$	(1, 2, 3)	(1, 2, 3)	(1, 3, 5)	(3, 5, 7)	(4, 6, 8)	(4, 6, 8)	(7, 9, 11)	(4, 6, 8)	(1, 3, 5)
$\tilde{c}^a_{33k}$	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(7, 8, 9)	(2, 3, 4)	(7, 9, 11)	(3, 5, 7)	(5, 7, 9)	(10, 11, 12)

Table 2: Parto solutions for average and optimistic cases

Optimistic case ($\alpha = 0$)			
$\tilde{z}_1$	$\tilde{z}_1$	$\tilde{z}_1$	$l = (l_1, l_2, l_3)$
67, 100, 133)	(97, 123, 149)	(82, 120, 158)	(83.5, 110, 101)
(75, 98, 121)	(87, 112, 137)	(70, 107, 139)	(86.5, 99.5, 88.5)
(71, 103, 135)	(78, 106, 134)	(70, 107, 144)	(87, 92, 91)
(75, 114, 153)	(50, 65, 80)	(48, 86, 124)	(94.5, 57.5, 67)
(89, 129, 169)	(95, 113, 131)	(52, 78, 104)	(109, 104, 65)
(89, 130, 171)	(48, 63, 78)	(90, 126, 162)	(109.5, 55.5, 108)
(103, 141, 179)	(43, 59, 75)	(83, 118, 153)	(122, 51, 105.5)
(109, 139, 169)	(115, 143, 171)	(47, 78, 109)	(124, 129, 62.5)
(106, 143, 180)	(42, 56, 70)	(61, 94, 127)	(124.5, 49, 77.5)
(117, 152, 187)	(38, 55, 72)	(76, 110, 144)	(134.5, 46.5, 93)
(134, 158, 182)	(116, 139, 162)	(40, 71, 102)	(146, 127.5, 55.5)
(136, 159, 182)	(114, 138, 162)	(47, 78, 109)	(147.5, 126, 62.5)
Moderate case ($\alpha = 0.5$)			
$\tilde{z}_1$	$\tilde{z}_2$	$\tilde{z}_3$	$l = (l_1, l_2, l_3)$
(73, 78, 123)	(132, 162, 192)	(105, 147, 189)	(98, 162, 147)
(74, 103, 137)	(100, 130, 160)	(86, 125, 164)	(103, 130, 125)
(71, 104, 137)	(94, 121, 148)	(80, 118, 156)	(104, 121, 118)
(73, 109, 145)	(53, 71, 89)	(48, 87, 126)	(109, 71, 87)
(75, 114, 153)	(50, 65, 80)	(48, 86, 124)	(114, 65, 86)
(81, 122, 163)	(46, 59, 72)	(60, 98, 136)	(122, 59, 98)
(128, 153, 178)	(125, 149, 173)	(41, 74, 107)	(153, 149, 74)
(130, 156, 182)	(100, 125, 150)	(36, 69, 102)	(156, 125, 69)

Optimistic case ($\alpha = 0$): $I^+ = (83.5, 46.5, 5.55)$ $I^- = (147, 129, 108)$; Moderate case ($\alpha = 0.5$): $I^+ = (98, 59, 69)$ $I^- = (156, 162, 147)$

$$\sum_{i=1}^{3}\sum_{j=1}^{3} x_{ij1} = 10,\ \sum_{i=1}^{3}\sum_{j=1}^{3} x_{ij2} = 5,\ \sum_{i=1}^{3}\sum_{j=1}^{3} x_{ij3} = 6$$

$$x_{ijk} \geq 0 \quad \forall_i = 1, 2, 3,\ j = 1, 2, 3,\ k = 1, 2, 3$$

Representation of chromosomes: In conventional evolutionary algorithms, chromosomes are commonly represented as binary strings. In this study, however, chromosome is represented as a sequence of integers which is designed as following:

$$X = \begin{pmatrix} x_{111}, x_{112}, x_{113}, x_{121}, x_{122}, x_{123}, x_{131}, x_{132}, x_{133} \\ x_{211}, x_{212}, x_{213}, x_{221}, x_{222}, x_{223}, x_{231}, x_{232}, x_{233} \\ x_{311}, x_{312}, x_{313}, x_{321}, x_{322}, x_{323}, x_{331}, x_{332}, x_{333} \end{pmatrix}$$

So, X_{ijk} at first should randomly be designed to go for all the limitations of the problem. In this example, fix parameters are max_gen = 1000, pop_size = 30, $p_m = 0.2$, $w_1 = 0$, $w_2 = 0$ and $w_3 = 0$. Pareto solutions are implemented more than ten times are shown in Table 2 for average and optimistic cases (Abd El-Wahed and Lee, 2006) and the best compromise solutions for each case is marked by*. Solution that is obtained for optimistic case (a = 0) is:

$$x_{121} = 6, x_{331} = 4, x_{132} = 2, x_{232} = 2, x_{332} = 1, x_{213} = 7$$

Solution that is obtained for average case (a = 0.5) is:

$$x_{121} = 5, x_{331} = 5, x_{122} = 1, x_{132} = 2, x_{232} = 2, x_{213} = 7$$

CONCLUSION

As a result the model has gotten a complete fuzzy state. To solve the problem, at first complete fuzzy solution methods and then a specific hybrid evolutionary algorithm are used to get the best solution which their results are presented in the last section of the study.

REFERENCES

Abd El-Wahed, W.F. and S.M. Lee, 2006. Interactive fuzzy goal programming for multi-criteria transportation problems. Omega, 34: 158-166.

Abd El-Wahed, W.F., 2001. A multi-criteria transportation problem under fuzziness. Fuzzy Sets Syst., 117: 27-33.

Amid, A., S.H. Ghodsypour and C. O'Brien, 2006. Fuzzy multiobjective linear model for supplier selection in a supply chain. Int. J. Produc. Econ., 104: 394-407.

Cadenas, J.M. and J.L. Verdegay, 1997. Using fuzzy numbers in linear programming. Syst. Man Cybern., 27: 1016-1022.

Chen, S.P. and P.C. Chang, 2006. A mathematical programming approach to supply chain models with fuzzy parameters. Eng. Optimization, 38: 647-669.

Chern, C.C., Y.L. Chen and L.C. Kung, 2010. A heuristic relief transportation planning algorithm for emergency supply chain management. Int. J. Comput. Math, 87: 1638-1664.

Dubois, D., H. Fargier and P. Fortemps, 2003. Fuzzy scheduling: Modelling flexible constraints vs. coping with incomplete knowledge. Eur. J. Operat. Res., 147: 231-252.

Fogel, D.B., 1994. An introduction to simulated evolutionary optimization. IEEE Trans. Neural Networks, 5: 3-14.

Haghani, A. and S.C. Oh, 1996. Formulation and solution of a multi-commodity, multi-modal network flow model for disaster relief operations. Transp. Res., 30: 231-250.

Jimenez, M., M. Arenas, A. Bilbao and M.V. Guez, 2007. Linear programming with fuzzy parameters: An interactive method resolution. Eur. J. Operat. Res., 177: 1599-1609.

Karabuk, S., 2007. Modeling and optimizing transportation decisions in a manufacturing supply chain. Transp. Res. Logist. Transp. Rev., 43: 321-337.

Teodorovici, D., 2007. Swarm: Principles and applications. Transp. Res. Emerg. Technol., 16: 651-667.

Vasant, P.M., 2005. Fuzzy linear programming for decision making and planning under uncertainty. Int. J. Inf. Technol. Decis. Making, 4: 647-662.

Vignaux, G.A. and Z. Michalewicx, 1991. A genetic algorithm for the linear transportation problem. IEEE Trans. Syst. Man. Cybern., 21: 445-452.

Yang, L. and Y. Feng, 2007. A bicriteria solid transportation problem with fixed charge under Stochastic environment. Appl. Math. Model., 31: 2668-2683.