2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)
July 6-11, 2014, Beijing, China

Situation-Based Allocation of Medical Supplies in Unconventional Disasters with Fuzzy Triangular Values

Junhu Ruan[1,2]
[1]Institute of Systems Engineering
Dalian University of Technology
Dalian, China
Email: ruanjunhu@mail.dlut.edu.cn
[2]School of Electrical and Electronic Engineering
University of Adelaide
Adelaide, Australia
Email: junhu.ruan@adelaide.edu.au

Yan Shi[1,3]
[3]School of Industrial Engineering
Tokai University
Kumamoto, Japan
Email: yshi@ktmail.tokai-u.jp

***Abstract*—Prompt medical service and supplies are very important to reduce the life loss in response to disasters. In this work, we focus on how to allocate the limited medical supplies to affected areas in different situations with fuzzy triangular values. Using the α-cut method and Giove's acceptability index, we first propose a method of comparing fuzzy triangular numbers. Then, based on our previous work, we develop a situation-based approach for allocating medical supplies with fuzzy triangular values. A simple example shows the effectiveness of the developed approach.**

I. INTRODUCTION

The unconventional disasters, such as earthquakes, hurricanes and infectious diseases, often disrupt the preparation of emergency decision-makers, pushing them in disorientated situations. In response to these disasters, prompt medical service and supplies are very important to reduce the life loss [1]-[2]. However, it is a challenge to properly allocate scarce medical supplies to affected areas in different situations due to the following characteristics:

(1) The surged demands for medical supplies far exceed the limited supplies at the initial response stage [3]-[4], so the available medical supplies are often allocated proportionately to different affected areas.

(2) The situations in different affected areas are various, which result in different demands for medical supplies, and the situations often involve multiple factors in different dimensionalities such as disaster levels and trapped populations [5].

(3) The information of the situation factors is not always precise (crisp) due to the uncertainty and emergency of the disasters response [6]. When people face uncertain situations, they prefer to estimate the situation factors using interval or fuzzy values.

Motivated by this, we are focusing on how to proportionately allocate limited medical supplies in accord with the situations of different affected areas. In our previous work [3], we developed a situation-based method for allocating relief supplies in disasters where all the situation data were crisp values. In this work we extend the situation-based allocation method to deal with the situations with fuzzy triangular values.

The rest of this paper is organized as follows. Section 2 introduces a method of comparing fuzzy triangular numbers. In Section 3, we present the developed approach for allocating medical supplies when the situation information contains fuzzy triangular values. Section 4 illustrates a simple example to show the feasibility of this approach. Conclusions are finally drawn in Section 5, with recommendations in future studies.

II. A METHOD OF COMPARING FUZZY TRIANGULAR NUMBERS

As mentioned in the Introduction, our focused decision problem involves fuzzy triangular values, so it is necessary to determine how to compare fuzzy triangular values. Since Zadeh [7] proposed the concept of fuzzy sets, many researches on comparing fuzzy numbers have been reported. Please refer to [8]-[10] and the references therein for details. In this work, we first use the common α-cut method [11] to transfer fuzzy triangular values into interval values, and then compare them.

Assume that $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ are two fuzzy triangular numbers, their membership functions are respectively as follows:

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-a_1}{a_2-a_1}, a_1 \leq x \leq a_2 \\ \frac{x-a_2}{a_3-a_2}, a_2 \leq x \leq a_3 \end{cases} \tag{1}$$

$$\mu_{\tilde{b}}(x) = \begin{cases} \frac{x-b_1}{b_2-b_1}, b_1 \leq x \leq b_2 \\ \frac{x-b_2}{b_3-b_2}, b_2 \leq x \leq b_3 \end{cases} \tag{2}$$

By the α-cut method, the α-cuts of $\tilde{a}$ and $\tilde{b}$ are two crisp interval numbers:

$$\tilde{a}_\alpha = [(a_2 - a_1)\alpha + a_1, a_3 - (a_3 - a_2)\alpha] \tag{3}$$

$$\tilde{b}_\alpha = [(b_2 - b_1)\alpha + b_1, b_3 - (b_3 - b_2)\alpha] \tag{4}$$

where $0 \leq \alpha \leq 1$. The α level to some extent denotes the truth level, so in this work we take $\alpha \geq 0.6$.

On how to compare two interval numbers, Sengupta et al [12] defined an acceptability index, and then Giove [13] modified the index. In this work, we not only compare two fuzzy numbers but also compare two crisp numbers, so the Giove's acceptability index is used, that is,

$$\xi(\tilde{a}_\alpha \succ \tilde{b}_\alpha) = \frac{m(\tilde{a}_\alpha) - m(\tilde{b}_\alpha)}{w(\tilde{a}_\alpha) + w(\tilde{b}_\alpha) + 1} \tag{5}$$

where

$$m(\tilde{a}_\alpha) = \frac{1}{2}(((a_2 - a_1)\alpha + a_1) + (a_3 - (a_3 - a_2)\alpha)) \tag{6}$$

and

$$m(\tilde{b}_\alpha) = \frac{1}{2}(((b_2 - b_1)\alpha + b_1) + (b_3 - (b_3 - b_2)\alpha)) \tag{7}$$

are the mid-points of $\tilde{a}_\alpha$ and $\tilde{b}_\alpha$ respectively, and

$$w(\tilde{a}_\alpha) = \frac{1}{2}((a_3 - (a_3 - a_2)\alpha) - ((a_2 - a_1)\alpha + a_1)) \tag{8}$$

and

$$w(\tilde{b}_\alpha) = \frac{1}{2}((b_3 - (b_3 - b_2)\alpha) - ((b_2 - b_1)\alpha + b_1)) \tag{9}$$

are the half-widths of $\tilde{a}_\alpha$ and $\tilde{b}_\alpha$.

III. A Situation-Based Approach for Allocating Medical Supplies with Fuzzy Triangular Values

Assume that there are n medical aid points (MAPs) $A_1, A_2, ..., A_n$ in a disaster, and there are m situation factors influencing the allocation of medical supplies. Thus, the situations of these MAPs can be represented by a matrix of situation factors $S = \left[\tilde{f}_j^i\right]_{n \times m}, i = 1, 2, ..., m, j = 1, 2, ..., n$ where $\tilde{f}_j^i = ((f_j^i)_1, (f_j^i)_2, (f_j^i)_3)$. The quantity of available medical supplies is S. Based on our previous work [3], we develop the following approach for allocating medical supplies proportionately in accord with the situations of these MAPs when the situation factors contain fuzzy triangular values.

The m situation factors may be in different dimensionalities, so we first make them dimensionless by normalizing them. For any fuzzy situation factor $\tilde{f}_j^i = ((f_j^i)_1, (f_j^i)_2, (f_j^i)_3), j = 1, 2, ..., n$, its normalized value is:

$$\begin{aligned} \overline{\tilde{f}_j^i} = (\overline{(f_j^i)_1}, \overline{(f_j^i)_2}, \overline{(f_j^i)_3}) = (&\tfrac{(f_j^i)_1 - \min((f_j^i)_1)}{\max((f_j^i)_3) - \min((f_j^i)_1)}, \\ &\tfrac{(f_j^i)_2 - \min((f_j^i)_1)}{\max((f_j^i)_3) - \min((f_j^i)_1)}, \tfrac{(f_j^i)_3 - \min((f_j^i)_1)}{\max((f_j^i)_3) - \min((f_j^i)_1)}) \end{aligned} \tag{10}$$

where $\min((f_j^i)_1)$ and $\max((f_j^i)_3)$ respectively return the minimum of $\{(f_j^i)_1, j = 1, 2, ..., n\}$ and the maximum of $\{(f_j^i)_3, j = 1, 2, ..., n\}$.

By Equation (3), we can get the α-cuts of the normalized $\overline{\tilde{f}_j^i}$:

$$(\overline{\tilde{f}_j^i})_\alpha = [(\overline{(f_j^i)_2} - \overline{(f_j^i)_1})\alpha + \overline{(f_j^i)_1}, \overline{(f_j^i)_3} - (\overline{(f_j^i)_3} - \overline{(f_j^i)_2})\alpha] \tag{11}$$

Then, we use the Giove's acceptability index to define the *Relative Demand Increment (RDI)* of any $(\overline{\tilde{f}_j^i})_\alpha$ over other values on the term of the same situation factor:

$$\begin{aligned} RDI((\overline{\tilde{f}_j^i})_\alpha) &= \sum_{\substack{k=1 \\ k \neq j}}^{n} \xi((\overline{\tilde{f}_j^i})_\alpha \succ (\overline{\tilde{f}_k^i})_\alpha) \\ &= \sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{m((\overline{\tilde{f}_j^i})_\alpha) - m((\overline{\tilde{f}_k^i})_\alpha)}{w((\overline{\tilde{f}_j^i})_\alpha) + w((\overline{\tilde{f}_k^i})_\alpha) + 1}, \forall i \in \{1, 2, ...m\} \end{aligned} \tag{12}$$

where

$$\begin{aligned} m((\overline{\tilde{f}_j^i})_\alpha) = \tfrac{1}{2}((((&\overline{(f_j^i)_2} - \overline{(f_j^i)_1})\alpha + \overline{(f_j^i)_1}) + \\ &(\overline{(f_j^i)_3} - (\overline{(f_j^i)_3} - \overline{(f_j^i)_2})\alpha)) \end{aligned} \tag{13}$$

$$\begin{aligned} w((\overline{\tilde{f}_j^i})_\alpha) = \tfrac{1}{2}((&\overline{(f_j^i)_3} - (\overline{(f_j^i)_3} - \overline{(f_j^i)_2})\alpha) - \\ &(((\overline{(f_j^i)_2} - \overline{(f_j^i)_1})\alpha + \overline{(f_j^i)_1})) \end{aligned} \tag{14}$$

$$\begin{aligned} m((\overline{\tilde{f}_k^i})_\alpha) = \tfrac{1}{2}((((&\overline{(f_k^i)_2} - \overline{(f_k^i)_1})\alpha + \overline{(f_k^i)_1}) + \\ &(\overline{(f_k^i)_3} - (\overline{(f_k^i)_3} - \overline{(f_k^i)_2})\alpha)) \end{aligned} \tag{15}$$

$$\begin{aligned} w((\overline{\tilde{f}_k^i})_\alpha) = \tfrac{1}{2}((&\overline{(f_k^i)_3} - (\overline{(f_k^i)_3} - \overline{(f_k^i)_2})\alpha) - \\ &(((\overline{(f_k^i)_2} - \overline{(f_k^i)_1})\alpha + \overline{(f_k^i)_1})) \end{aligned} \tag{16}$$

After calculating the RDI of each MAP A_j, we can determine the best and worst situations [3] [14]:

$$S^* = \{RDI((\overline{\tilde{f}_j^1})_\alpha)^*, RDI((\overline{\tilde{f}_j^2})_\alpha)^*, ..., RDI((\overline{\tilde{f}_j^m})_\alpha)^*\} \tag{17}$$

$$S_* = \{RDI((\overline{\tilde{f}_j^1})_\alpha)_*, RDI((\overline{\tilde{f}_j^2})_\alpha)_*, ..., RDI((\overline{\tilde{f}_j^m})_\alpha)_*\} \tag{18}$$

where

$$\begin{aligned} RDI((\overline{\tilde{f}_j^i})_\alpha)^* = \min(&RDI((\overline{\tilde{f}_1^i})_\alpha), RDI((\overline{\tilde{f}_2^i})_\alpha), \\ &..., RDI((\overline{\tilde{f}_n^i})_\alpha)) \end{aligned} \tag{19}$$

$$\begin{aligned} RDI((\overline{\tilde{f}_j^i})_\alpha)_* = \max(&RDI((\overline{\tilde{f}_1^i})_\alpha), RDI((\overline{\tilde{f}_2^i})_\alpha), \\ &..., RDI((\overline{\tilde{f}_n^i})_\alpha)) \end{aligned} \tag{20}$$

Further, we could calculate the distance of the situation of any MAP from the best situation:

$$\begin{aligned} D_{j1} = distance(&\{RDI((\overline{\tilde{f}_j^1})_\alpha), ..., RDI((\overline{\tilde{f}_j^m})_\alpha)\}, \\ &\{RDI((\overline{\tilde{f}_j^1})_\alpha)^*, ..., RDI((\overline{\tilde{f}_j^m})_\alpha)^*\}) \end{aligned} \tag{21}$$

and the distance from the worst situation:

$$\begin{aligned} D_{j2} = distance(&\{RDI((\overline{\tilde{f}_j^1})_\alpha), ..., RDI((\overline{\tilde{f}_j^m})_\alpha)\}, \\ &\{RDI((\overline{\tilde{f}_j^1})_\alpha)_*, ..., RDI((\overline{\tilde{f}_j^m})_\alpha)_*\}) \end{aligned} \tag{22}$$

In this work, the weighted Euclidean distance is used, that is, for any MAP A_j,

$$D_{j1} = \sqrt{\sum_{i=1}^{m} w_i (RDI((\overline{\tilde{f}_j^i})_\alpha) - RDI((\overline{\tilde{f}_j^i})_\alpha)^*)^2} \tag{23}$$

$$D_{j2} = \sqrt{\sum_{i=1}^{m} w_i (RDI((\overline{\tilde{f}_j^i})_\alpha) - RDI((\overline{\tilde{f}_j^i})_\alpha)_*)^2} \tag{24}$$

where $W = [w_1, w_2, ..., w_m]$ denotes the weights vector of the situation factors.

In order to measure the closeness of some situation to the worst and best situations, the following relative similarity is used:

$$Q_j = \frac{D_{j1}}{D_*^*} = \frac{\sqrt{\sum_{i=1}^{m} w_i(RDI((\overline{\tilde{f}_j^i})_\alpha) - RDI((\overline{\tilde{f}_j^i})_\alpha)^*)^2}}{\sqrt{\sum_{i=1}^{m} w_i(RDI((\overline{\tilde{f}_j^i})_\alpha)_* - RDI((\overline{\tilde{f}_j^i})_\alpha)^*)^2}} \tag{25}$$

where

$$D_*^* = \sqrt{\sum_{i=1}^{m} w_i(RDI((\overline{\tilde{f}_j^i})_\alpha)_* - RDI((\overline{\tilde{f}_j^i})_\alpha)^*)^2} \tag{26}$$

denotes the distance of the best situation and the worst situation. The greater the Q_j of MAP A_j is, the more medical supplies the MAP needs.

Thus, the allocated proportion of medical supplies for MAP A_j should be

$$R_j = \frac{Q_j}{\sum_{j=1}^{n} Q_j} \tag{27}$$

Finally, the allocated quantity of medical supplies for MAP A_j:

$$S_j = R_j S \tag{28}$$

where S represents the total available quantity of vaccines.

IV. An Illustrative Example

To show the feasibility of the developed approach, we illustrate a simple example in this Section. In some infectious disaster, 10 MAPs are set up which are in different situations. A batch of vaccines (10,000 doses) is available, which is not enough for the actual demand of all the MAPs. Emergency decision-makers are considering the following six situation factors to allocate the available vaccines: (1) f_j^1 : The infectious rate per 100 persons in the affected area covered by MAP A_j; (2) f_j^2 : The hospitalization rate per 100 cases in the affected area covered by MAP A_j; (3) f_j^3 : The fatality rate per 100 cases in the affected area covered by MAP A_j; (4) f_j^4 : The number of children and elderly population in the affected area covered by MAP A_j; (5) f_j^5 : The number of the total population in the affected area covered by MAP A_j; (6) f_j^6 : The average contact time between individuals in the affected area covered by MAP A_j.

Table I gives the randomly generated situations of the 10 MAPs, where the second row defines the range of each situation factor. Using the normalization Equation (10), we could get the normalized values, as Table 2 shows.

After normalizing the situations, we use the α-cut method to obtain the interval values with high confidence levels of the fuzzy triangular numbers in the situations. Here we set $\alpha = 0.6$. Take the f_j^1 of A_3 for example, the value is a fuzzy triangular (0.167, 0.278, 0.389) in Table II. Using the Equation (3), we get:

$$(\overline{\tilde{f}_3^1})_\alpha = [(0.278 - 0.167) \times 0.6 + 0.167, \\ 0.389 - (0.389 - 0.278) \times 0.6] = [0.233, 0.322]$$

In the same way, the other values in Table III could be obtained. Then, using the Giove's acceptability index, we calculate the RDI of any $(\overline{\tilde{f}_j^i})_\alpha$ in Table III, as Table IV shows. Thus, the best and worst situations are got:

$$S^* = [\text{-4.378, -4.786, -4.750, -5.125, -4.382, -3.956}]$$

$$S_* = [\text{4.867, 5.214, 5.250, 4.875, 5.178, 3.939}]$$

Using Equations (21)-(24) and (26), we could get the distances of any MAP from the best and worst situations, and the distance between the best and worst situations, as the second, third and fourth columns in Table V show (Here the weights of the six factors are set the same, that is, $W = [w_1, w_2, ..., w_6] = [1/6, 1/6, ..., 1/6]$). Finally, we calculate the relative similarities, the allocated proportions and the allocated vaccine quantities for all the MAPs, as the last three columns show.

By comparing the original situations of these MAPs and the allocated results, we could test the effectiveness of the developed approach. For example, the original situations of MAP A_1 and MAP A_2 are as follows:

$$S_1 = [0.43, 0.15, 0.03, 1470, (5400, 5500, 5600), (4, 6, 8)]$$

$$S_2 = [0.40, 0.12, 0.03, 1464, (5300, 5400, 5500), (3, 5, 7)]$$

As we can see, the situation of MAP A_1 is a little worst than that of MAP A_2, so more vaccines should be allocated to MAP A_1 in term of the fairness. Actually, the developed approach allocates 989 doses of vaccines to MAP A_1 which is a little more than the 913 doses to MAP A_2.

In order to show the effectiveness, we compare the allocation results in Table V with those produced by the method in [3], as Fig.1 shows. Note that, the method in [3] can not deal with fuzzy values, so we take the crisp values with membership degree being 1 in Table I (that is, the $(f_j^i)_2$) as the factor values for the method in [3]. Seen from the comparison, we can see the allocation results by the proposed approach are basically consistent with those by the method in [3], which tests the effectiveness of the proposed approach for dealing with fuzzy triangular values.

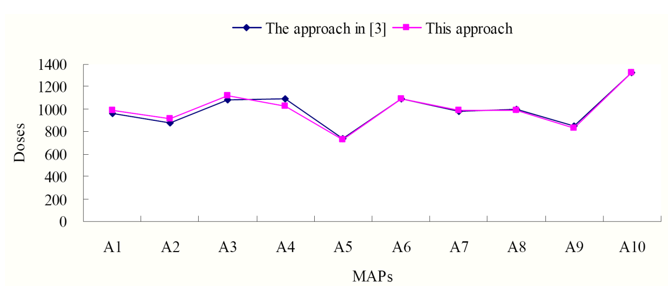

Fig. 1. The Comparison with [3]

TABLE I. THE SITUATIONS OF MAPS

MAPs	f_j^1	f_j^2	f_j^3	f_j^4	f_j^5	f_j^6
	[0.3,0.6]	[0.1,0.3]	[0,0.1]	[600,2000]	[2000,10000]	[5,30]
A_1	0.43	0.15	0.03	1470	(5400,5500,5600)	(4,6,8)
A_2	0.40	0.12	0.03	1464	(5300,5400,5500)	(3,5,7)
A_3	(0.33,0.35,0.37)	0.17	0.08	1474	(3100,3300,3500)	(11,15,17)
A_4	0.41	0.15	0.03	997	(8200,8500,8600)	(25,28,30)
A_5	(0.40,0.44,0.46)	0.21	0.01	1036	(2900,2950,3000)	(5,8,10)
A_6	0.48	0.22	0.06	859	(2500,2600,2700)	(16,19,22)
A_7	(0.30,0.32,0.35)	0.22	0.06	1173	(5600,5700,5800)	(17,19,21)
A_8	0.42	0.21	0.01	862	(8300,8600,8800)	(15,18,20)
A_9	(0.32,0.34,0.37)	0.16	0.00	1396	(3700,3900,4000)	(20,22,25)
A_{10}	0.31	0.26	0.07	1011	(8900,9000,9100)	(22,25,27)

TABLE II. THE NORMALIZED SITUATIONS OF MAPS

MAPs	f_j^1	f_j^2	f_j^3	f_j^4	f_j^5	f_j^6
A_1	0.722	0.214	0.375	0.993	(0.439,0.455,0.470)	(0.037,0.111,0.185)
A_2	0.556	0.000	0.375	0.984	(0.424,0.439,0.455)	(0.000,0.074,0.148)
A_3	(0.167,0.278,0.389)	0.357	1.000	1.000	(0.091,0.121,0.152)	(0.296,0.444,0.519)
A_4	0.611	0.214	0.375	0.224	(0.864,0.909,0.924)	(0.815,0.926,1.000)
A_5	(0.556,0.778,0.889)	0.643	0.125	0.288	(0.061,0.068,0.076)	(0.074,0.185,0.259)
A_6	1.000	0.714	0.750	0.000	(0.000,0.015,0.030)	(0.481,0.593,0.704)
A_7	(0.000,0.111,0.278)	0.714	0.750	0.511	(0.470,0.485,0.500)	(0.519,0.593,0.667)
A_8	0.667	0.643	0.125	0.005	(0.879,0.924,0.955)	(0.444,0.556,0.630)
A_9	(0.111,0.222,0.389)	0.286	0.000	0.873	(0.182,0.212,0.227)	(0.630,0.704,0.815)
A_{10}	0.056	1.000	0.875	0.247	(0.970,0.985,1.000)	(0.704,0.815,0.889)

TABLE III. THE α-CUTS OF THE NORMALIZED SITUATIONS

MAPs	f_j^1	f_j^2	f_j^3	f_j^4	f_j^5	f_j^6
A_1	0.722	0.214	0.375	0.993	[0.448, 0.461]	[0.081, 0.141]
A_2	0.556	0.000	0.375	0.984	[0.433, 0.445]	[0.044, 0.104]
A_3	[0.233, 0.322]	0.357	1.000	1.000	[0.109, 0.133]	[0.385, 0.474]
A_4	0.611	0.214	0.375	0.224	[0.891, 0.915]	[0.881, 0.956]
A_5	[0.689, 0.822]	0.643	0.125	0.288	[0.065, 0.071]	[0.141, 0.215]
A_6	1.000	0.714	0.750	0.000	[0.009, 0.021]	[0.548, 0.637]
A_7	[0.067, 0.178]	0.714	0.750	0.511	[0.479, 0.491]	[0.563, 0.622]
A_8	0.667	0.643	0.125	0.005	[0.906, 0.936]	[0.511, 0.585]
A_9	[0.178, 0.289]	0.286	0.000	0.873	[0.200, 0.218]	[0.674, 0.748]
A_{10}	0.056	1.000	0.875	0.247	[0.979, 0.991]	[0.770, 0.844]

TABLE IV. THE RDIS, THE BEST SITUATION AND THE WORST SITUATION

MAPs	f_j^1	f_j^2	f_j^3	f_j^4	f_j^5	f_j^6
A_1	2.148	-2.643	-1.000	4.810	-0.050	-3.609
A_2	0.516	-4.786	-1.000	4.712	-0.200	-3.956
A_3	-2.110	-1.214	5.250	4.875	-3.317	-0.612
A_4	1.060	-2.643	-1.000	-2.881	4.346	3.939
A_5	2.324	1.643	-3.500	-2.247	-3.871	-2.963
A_6	4.867	2.357	2.750	-5.125	-4.382	0.896
A_7	-3.532	2.357	2.750	-0.020	0.249	0.908
A_8	1.604	1.643	-3.500	-5.076	4.511	0.488
A_9	-2.500	-1.929	-4.750	3.607	-2.463	2.006
A_{10}	-4.378	5.214	4.000	-2.654	5.178	2.903
The best situation S^*	-4.378	-4.786	-4.750	-5.125	-4.382	-3.956
The worst situation S_*	4.867	5.214	5.250	4.875	5.178	3.939

TABLE V. THE FINAL ALLOCATION RESULTS

MAPs	D_{j1}	D_{j2}	D_*^*	Q_j	R_j	S_j
A_1	5.460	5.664	9.480	0.576	0.099	989
A_2	5.038	6.446	9.480	0.531	0.091	913
A_3	6.194	5.521	9.480	0.653	0.112	1122
A_4	5.654	5.418	9.480	0.596	0.102	1024
A_5	4.028	6.783	9.480	0.425	0.073	730
A_6	6.004	5.987	9.480	0.633	0.109	1088
A_7	5.465	4.872	9.480	0.576	0.099	990
A_8	5.439	5.935	9.480	0.574	0.099	985
A_9	4.604	6.696	9.480	0.486	0.083	834
A_{10}	7.316	4.913	9.480	0.772	0.133	1325

V. CONCLUSION

In this work, we first proposed a simple method for comparing fuzzy triangular numbers, and then extended the situation-based allocation approach to deal with the disaster situations with fuzzy values. The illustrated example showed that the extended approach is effective to allocate limited medical supplies to MAPs in different situations with fuzzy triangular values. However, further studies are needed to perfect this approach, such as the determination of the factor weights and the consideration of decision-maker's preferences.

ACKNOWLEDGMENT

This research is supported by National Natural Science Foundation of China (No. 90924006, 71171029), the China Scholarship Council, and Fundamental Research Funds for the Central Universities of China. The authors would also like to thank three anonymous referees whose suggestions greatly improve this work.

REFERENCES

[1] H. Z. Jia, F. Ordóñez, and M. M. Dessouky, "Solution approaches for facility location of medical supplies for large-scale emergencies", *Computers & Industrial Engineering,* vol. 52, no. 2, pp. 257-276, Mar. 2007.

[2] H. O. Mete and Z. B. Zabinsky, "Stochastic optimization of medical supply location and distribution in disaster management", *International Journal of Production Economics,* vol. 126, no. 1, pp. 76-84, July 2010.

[3] J. H. Ruan, X. P. Wang, and Y. Shi, "Scenario-based allocating of relief medical supplies for large-scale disasters", *ICIC Express Letters*, vol. 7, no. 2, pp. 471-478, Feb. 2013.

[4] H. Arora, T. S. Raghu, and A. Vinze, "Resource allocation for demand surge mitigation during disaster response", *Decision Support Systems*, vol. 50, no. 1, pp. 304-315, Dec. 2010.

[5] Y. Peng and L. A. Yu, "Multiple criteria decision making in emergency management", *Computers & Operations Research*, vol. 42, pp. 1-2, Feb. 2014.

[6] H. Yarmand, J. S. Ivy, B. Denton, and A. L. Lloy, "Optimal two-phase vaccine allocation to geographically different regions under uncertainty", *European Journal of Operational Research*, vol. 233, no. 1, pp. 208–219, Feb. 2014.

[7] L. A. Zadeh, "Fuzzy sets", *Information and Control*, vol. 8, no. 3, pp. 338-353, June 1965.

[8] L. Tran and L. Duckstein, "Comparison of fuzzy numbers using a fuzzy distance measure", *Fuzzy Sets and Systems*, vol. 130, no. 3, pp. 331-341, Sep. 2002.

[9] V. N. Huynh, Y. Nakamori, and J. Lawry, "A probability-based approach to comparison of fuzzy numbers and applications to target-oriented decision making", *IEEE Transactions on Fuzzy Systems*, vol. 16, no. 2, pp. 371-387, Apr. 2008.

[10] V. F. Yu, H. T. X. Chi, and C. W. Shen, "Ranking fuzzy numbers based on epsilon-deviation degree", *Applied Soft Computing*, vol. 13, no. 8, pp. 3621-3627, Aug. 2013.

[11] W. L. Hung and J. W. Wu, "Correlation of fuzzy numbers by α-cut method", *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, vol. 10, no. 6, pp. 725-735, Dec. 2002.

[12] A. Sengupta, T. K. Pal, and D. Chakraborty, "Interpretation of inequality constraints involving interval coefficients and a solution to interval linear programming", *Fuzzy Sets and Systems*, vol. 119, no. 1, pp. 129-138, Apr. 2001.

[13] S. Giove, "Interval TOPSIS for multicriteria decision making", *Neural Nets, Lecture Notes in Computer Science,* vol. 2486, pp. 56-63, 2002.

[14] J. H. Ruan, X. P. Wang, Y. Shi, and Z. L. Sun, "Scenario-based path selection in uncertain emergency transportation networks", *International Journal of Innovative Computing, Information and Control*, vol. 9, no. 8, pp. 3293-3305, Aug. 2013.