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New Fuzzy MADM Approach for the Temporary Logistics Hubs' Selection Preferences Identification in Disaster Region

Gia Sirbiladze[a], Bezhan Ghvaberidze[a], Bidzina Midodashvili[a], Irina Khutsishvili[a*], Bidzina Matsaberidze[a] and Teimuraz Manjafarashvili[a]

[a]*Department of Computer Sciences, I. Javakhishvili Tbilisi State University, 13 University St., 0186, Tbilisi, Georgia*
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This paper represents two stage fuzzy methodology for the optimal planning of order of establishment of temporary logistics hubs (TLHs). At the first stage, a q-rung orthopair fuzzy TOPSIS approach for formation and representing of expert's knowledge on the parameters of the order of establishment of temporary logistics hubs is developed, when resources (mobile storage units used as TLHs) are limited. At the second stage, based on the constructed fuzzy TOPSIS aggregation a new objective function is formulated. Constructed criterion maximizes TLHs' total identification level of the order of establishment. This criterion together with second criterion - minimization of number of selected TLHs', creates the multi-objective facility location set covering problem. Two stage approach is illustrated by the simulation example of emergency temporary logistics hubs' selection preferences identification for a city in Georgia.

Keywords: Temporary logistics hub, q-rung orthopair fizzy sets, fuzzy TOPSIS, set covering problem, multi-objective optimization

AMS Subject Classification: 03E72, 28E10, 60A86, 62A86, 68T37.

1. Introduction

Effective disaster salvage requires implementing different disaster response facilities immediately after a disaster has occurred. Of the numerous types of facilities prevalent in humanitarian operations, this study focuses on those intended for relief distribution. These facilities can be categorized as permanent or temporary based on the length of their operational horizon. Permanent facilities operate before the disaster and have long or even infinite operational horizons, whereas temporary response facilities only operate once the location of the disaster is known and have a short operational horizon. While determining the location for a permanent facility is a strategic decision, doing so for a temporary facility is a tactical/operational decision with which decision makers are faced after a disaster.

The appropriateness of a logistics hub's location can determine the success or failure of a humanitarian relief operation. However, the unpredictability of disasters makes it difficult to ascertain the precise location of logistics hubs beforehand. Moreover, high inventory holding costs, as well as limited funds and operating resources, often restrict the number of permanent facilities. Therefore, the temporary nature of such facilities is an indispensable part of humanitarian relief operations

*Corresponding author. Email: irina.khutsishvili@tsu.ge

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[1]. A temporary logistics hub is defined as a place designated for the storing, sorting, consolidating, deconsolidating and distributing of emergency relief materials to disaster-affected areas in the short term. They act as an intermediator between the central warehouse or relief supply points and the affected areas in need of emergency relief.

A typical location problem includes ascertaining the number, spatial location and the allocation of demand for open facilities. However, locating TLHs during disaster response also requires determining the order of establishment of the facilities when resources are limited. Often mobile storage units that can be easily assembled, disassembled and transported are used as TLHs. Fire retardant, waterproof, rot proof and UV stabilized, these mobile storage units too are usually expensive to be stockpiled in large quantities. For example, during the initial response stage of the 2015 Nepal Earthquake, the number of mobile storage units available in country was limited, which resulted in the effective establishment of regional logistics hubs facing several hindrances, including delay and mobile storage units having insufficient capacity.

In location decision making, traditional network models take into account quantitative factors and aim to minimize the total cost or to maximize profitability or coverage. Non-quantitative criteria, such as work force qualifications, geographical characteristics and road networks, are also important in deciding location. In the aftermath of a disaster, the decision-making process typically involves multiple decision makers with varying interests and opinions. Indeed, the growing complexity and uncertainty of decision situations make it less and less possible for a decision maker to consider all the relevant aspects of a problem, thereby necessitating the participation of multiple experts in the decision-making process [2]. As such, achieving a proper balance among them is a significant challenge. Furthermore, disaster response operation in most emerging countries is resource constrained and requires the effective allocation of resources to ensure their effective utilization. While optimization approaches can be used for evaluating quantitative factors, this evaluation of qualitative factors is often accompanied by ambiguity and vagueness [3]. This is particularly so in the aftermath of a disaster, when the environment is chaotic, and there is limited information and time. Moreover, in [4] authors state that intangible factors can change a network configuration resulting from a mathematical model. Essentially, disaster managers have to make myriad reactive operational decisions to solve complex dilemmas with little to no information under immensely stressful conditions as they respond to emergencies. This highlights the need for a simple and inclusive methodology. Under these circumstances, an appropriate decision-making strategy would require that the resolutions and opinions of a group of decision makers be taken into account when evaluating the subjective and objective attributes in the TLH selection process.

This study seeks to address the gaps in the existing literature and aid in the decision-making process by developing *a two stage methodology* that determines the order of establishment of TLHs, and which considers location problems in doing so. *At the first stage*, a new fuzzy TOPSIS approach is proposed. In this stage, a fuzzy multi-attribute group decision making approach is used to determine the order of establishment of selected TLHs. *On the second stage*, an optimization model to determine the number and spatial location of the TLHs is created. Finally, as the humanitarian code of conduct dictates that humanitarian imperative comes first such that the prime motivation of response to disaster is to alleviate human suffering [5]. In line with the humanitarian code of conduct, the optimization model in the second stage optimizes total unsatisfied demand. This is in contrary to common approach of minimizing costs which has been adopted by recent studies [6–8] focusing on temporary facilities. Moreover, a personal interview with the logistics expert working in non-governmental organization stated that minimizing unsatisfied demand should be the primary objective as humanitarian operations are based on donations.

As such, the objectives, and contributions, of this study are threefold. Introducing the concept of the order of establishment of TLHs, this study develops and implements a new fuzzy TOPSIS methodology aimed at the effective utilization of mobile storage units when their availability is scarce. Second, this study shows that amalgamating an optimization model with the multi-attribute decision making approach enables the evaluation of both subjective and objective attributes, and has enhanced applicability to real-life scenarios. To support this methodology and contributions, this study implements a numerical illustration using data from a simulation real-life disaster.

Multi-attribute group decision making (MAGDM) is to find an optimal alternative that has the highest degree of satisfaction from a set of feasible alternatives characterized with multiple criteria, and these kinds of MAGDM problems arise in many real-world situations. Considering the inherent vagueness of human preferences as well as the objects being fuzzy and uncertain, Bellman and Zadeh [9] introduced the theory of fuzzy sets in the MAGDM problems. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) developed by Hwang and Yoon [10] is one of the most useful distance measures based classical approaches to multi-criteria/multi-attribute decision making (MCDM/MADM) problems. It is a practical and useful technique for ranking and selection of a number of externally determined alternatives through distance measures. The basic principle used in the TOPSIS is that the chosen alternative should have the shortest distance from positive-ideal solution (PIS) and farthest from the negative-ideal solution (NIS). There exists a large amount of literature involving TOPSIS theory and applications. In the TOPSIS, the performance ratings and the weights of the criteria are given as crisp values. In classical TOPSIS methods, crisp numerical values are used to express the performance rating and criteria weights. But human judgment, preference values and criteria weights are often ambiguous and cannot be represented using crisp numerical value in real-life situation. Resolve the ambiguity frequently arising in information from human judgment and preference, fuzzy set theory has been successfully used to handle imprecision and uncertainty in decision making problems. In this work a novel decision-making TOPSIS approach is developed to deal effectively with the interactive MCDM problems with q-rung orthopair fuzzy information [11, 12].

The remainder of this paper is organized as follows. Preliminary Concepts are provided in the next section. Section 3 presents the TLH location selection model based on new fuzzy TOPSIS approach, which determines the order of establishment of the selected facilities. For the optimal selection of TLHs bi-objective facility location set covering problem is created in Section 4. In Section 5 a numerical simulation example for the illustration of new two stage methodology is demonstrated. Finally, Section 6 discusses the contributions and conclusions of this study.

2. Preliminary concepts

Intuitionistic fuzzy sets (IFS) were introduced by Atanassov [13], as a generalization of Zadeh's fuzzy sets (FS). Because each element of IFS, as Intuitionistic fuzzy number (IFN) (μ, υ) is assigned a membership degree (μ), a non-membership degree (υ) and a hesitancy degree $(1 - \mu - \upsilon)$, IFS is more powerful in dealing with uncertainty and imprecision than FS. IFS theory has been widely studied and applied to a variety of areas. But an IFN (μ, υ) has a significant restriction - the sum of the degrees of membership and the non-membership is equal or less than 1. In some cases, a decision maker (DM) may provide data for some attribute that the sum of two degrees is greater than 1 $(\mu + \upsilon > 1)$. Yager in [14, 15] presented the concept of the Pythagorean fuzzy set (PFS) as extension of an IFS, where the pair of a Pythagorean fuzzy number (PFN) (μ, υ) has a less significant restrict - a square sum of the degrees of membership and the non-membership is equal or less than 1 $(\mu^2 + \upsilon^2 \leq 1)$. In general, for practical problems, the PFSs can decide significant ones that IFSs cannot do. Therefore, PFSs are more able to process uncertain information and solve complex decision-making problems. PFNs have much less, but significant restriction. When the evaluation psychology of a DM is too complicated and contradictory for complex decision making, the attribute's corresponding information is still difficult to express with PFNs. Recently, again Yager decided this problem in [11, 12]. He proposed concept of a q-rung orthopair fuzzy set (q-ROFS), where $q \geq 1$ and the sum of the qth power of the degrees of membership and the non-membership cannot be greater than 1. For a q-rung orthopair fuzzy number (q-ROFN) we have $(\mu^q + \upsilon^q \leq 1)$. It is obvious that the q-ROFSs are more general than IFSs and PFSs. The IFSs and PFSs are the special cases of the q-ROFSs when $q = 1$ and $q = 2$, respectively. Therefore, q-ROFNs are more convenient and able to describe DM's evaluation information than IFNs and PFNs.

Definition 2.1: [11] Let S a fixed ordinary set q-rung orthopair fuzzy set A on S be defined as membership grades:

$$A = \left\{ \frac{\langle s, \mu_A(s), \nu_A(s) \rangle}{s \in S} \right\}, \tag{1}$$

where the functions $\mu_A(s)$ indicates support for membership of s in A and $\nu_A(s)$ indicates support against membership of s in A, where

$$q \geq 1, \;\; 0 \leq \mu_A(s) \leq 1, \;\; 0 \leq \nu_A(s) \leq 1, \;\; 0 \leq (\mu_A(s))^q + (\nu_A(s))^q \leq 1. \tag{2}$$

$\mathrm{Hes}_q(s) = (1 - ((\mu_A(s))^q + (\nu_A(s))^q)^{1/q}$ is called a hesitancy associated with a q-rung orthopair membership grades and $\mathrm{Str}_q(s) = ((\mu_A(s))^q + (\nu_A(s))^q)^{1/q}$ is called a strength of commitment viewed at rung q.

In [11], Yager showed that Attanassov's intuitionistic fuzzy sets [3] are $q = 1$ -rung orthopair and Yager's Pythagorean fuzzy sets [14] are $q = 2$ -rung orthopair fuzzy sets. For convenience, the authors for every $s \in S$ called $\alpha = \langle s, \mu_\alpha(s), \nu_\alpha(s) \rangle$ a q-rung orthothair fuzzy number (q-ROFN) denoted by $\alpha = (\mu_\alpha, \nu_\alpha)$.

Let us denote by L the lattice of non-empty intervals $L = \{[a; b]/(a, b) \in [0, 1]^2, \; a \leq b\}$. The partial order relation $\leq_L$ is defined as

$[a;b] \leq_L [c;d] \Leftrightarrow a \leq c$ and $b \leq d$. The top and bottom elements are $\mathbf{1}_L = [1;1]$ and $0_L = [0;0]$, respectively. For the lattice of all q-ROFNs the corresponding partial order relation $\leq_{L_{\text{q-ROFNs}}}$ is defined as:

$$(\mu_1, \nu_1) \leq_{L_{\text{q-ROFNs}}} (\mu_2, \nu_2) \Leftrightarrow \mu_1 \leq \mu_2 \text{ and } \nu_1 \geq \nu_2. \tag{3}$$

The top and bottom elements are $1_{L_{\text{q-ROFNs}}} = (1;0)$ and $0_{L_{\text{q-ROFNs}}} = (0;1)$, respectively.

Definition 2.2: [11] Suppose $\alpha = (\mu_\alpha, \nu_\alpha)$ be a q-ROFN. a) A score function Sc of α is defined as

$$Sc(\alpha) = \mu_\alpha^q - \nu_\alpha^q; \tag{4}$$

b) An accuracy function Ac of α is defined as follows:

$$Ac(\alpha) = \mu_\alpha^q + \nu_\alpha^q. \tag{5}$$

Based on these definitions a comparison method of q-ROFNs (total order relation $\leq_t$ on the lattice $L_{q-\text{ROFNs}}$) is defined.

Definition 2.3: [11] Suppose $\alpha = (\mu_\alpha, \nu_\alpha)$ and $\beta = (\mu_\beta, \nu_\beta)$ are any two q-ROFNs and $Sc(\alpha), Sc(\beta)$ are the score functions and $Ac(\alpha), Ac(\beta)$ are the accuracy functions of α and β, respectively, then

$$\begin{array}{ll} \text{a)} & \text{If } Sc(\alpha) > Sc(\beta), \text{ then } \beta <_t \alpha; \\ \text{b)} & \text{If } Sc(\alpha) = Sc(\beta), \text{ then} \\ & \qquad \text{If } Ac(\alpha) > Ac(\beta), \text{ then } \beta <_t \alpha; \\ & \qquad \text{If } Ac(\alpha) = Ac(\beta), \text{ then } \beta =_t \alpha. \end{array} \tag{6}$$

On the lattice $L_{q-\text{ROFNs}}$ the following basic operations can be defined.

Definition 2.4: [6] Suppose for $\alpha = (\mu_\alpha, \nu_\alpha)$, $\alpha_1, \alpha_2 \in L_{q-\text{ROFNs}}$ we have:

$$\begin{array}{l} 1.\ \alpha^c = (\nu_\alpha, \mu_\alpha); \\ 2.\ \alpha_1 \oplus_q \alpha_2 = \left((\mu_{\alpha_1}^q + \mu_{\alpha_2}^q - \mu_{\alpha_1}^q \cdot \mu_{\alpha_2}^q)^{1/q},\ \nu_{\alpha_1} \cdot \nu_{\alpha_2} \right); \\ 3.\ \alpha_1 \otimes_q \alpha_2 = \left(\mu_{\alpha_1} \cdot \mu_{\alpha_2},\ (\nu_{\alpha_1}^q + \nu_{\alpha_2}^q - \nu_{\alpha_1}^q \cdot \nu_{\alpha_2}^q)^{1/q} \right); \\ 4.\ Min(\alpha_1, \alpha_2) = (\min(\mu_{\alpha_1}, \mu_{\alpha_2}),\ \max(\nu_{\alpha_1}, \nu_{\alpha_2})); \\ 5.\ Max(\alpha_1, \alpha_2) = (\max(\mu_{\alpha_1}, \mu_{\alpha_2}),\ \min(\nu_{\alpha_1}, \nu_{\alpha_2})); \\ 6.\ \lambda \cdot \alpha = \left((1 - (1 - \mu_\alpha^q)^\lambda)^{1/q},\ \nu_\alpha^\lambda \right), \quad \lambda > 0; \\ 7.\ \alpha^\lambda = \left(\mu_\alpha^\lambda,\ (1 - (1 - \nu_\alpha^q)^\lambda)^{1/q} \right), \quad \lambda > 0. \end{array} \tag{7}$$

We define the distance between q-ruing orthopiar fuzzy numbers $\alpha_1, \alpha_2 \in$

$L_{q-\mathrm{ROFNs}}$:

$$d_q(\alpha_1, \alpha_2) = 1/2 \cdot (|(\mu_{\alpha_1})^q - (\mu_{\alpha_2})^q + |(\nu_{\alpha_1})^q - (\nu_{\alpha_2})^q|). \tag{8}$$

It is not difficult to prove that this measure satisfies all properties of a distance function.

3. Description of Fuzzy TOPSIS approach for the identifying the order of establishment of TLHs under Q-rung orthopair Fuzzy information

Timely servicing from emergency service centers to the affected geographical areas (demand points as customers, for example critical infrastructure objects) is a key task of the emergency management system. Scientific research in this area focuses on distribution networks decision-making problems, which are known as a general direction - Facility Location Problem (FLP) [16]. In our case, FLP's models have to support the generation of optimal locations of TLHs in complex and uncertain situations. There are several publications about application of fuzzy methods in the FLP. However, all of them have a common approach. They represent parameters as fuzzy values (triangular fuzzy numbers [17] and others) and develop methods for facility location problems called in this case Fuzzy Facility Location Problem (FFLP). Fuzzy TOPSIS approaches for facility location selection problem for different fuzzy environments are developed in [18–23]. Different Problems on fuzzy facility location selection problem are considered by the authors of this work in [24–29]. In this work we consider a new model of MAGDM based on the q-rung orthopair fuzzy TOPSIS approach the TLHs' Selection Preferences Identification. This section first introduces the MAGDM problem under q-rung orthopair fuzzy environment. Then, an effective decision-making approach is proposed to deal with such MAGDM problems. At length, an algorithm of the proposed method is also presented

At the first stage, we are focusing on a multi-attribute decision making approach for the identifying the order of establishment of TLHs under uncertain and extreme environment.

The formation of expert's input data for construction of attributes is an important task of the centers' selection problem. To decide on the location of service centers, it is assumed that a set of *candidate TLHs already exists.* This set is denoted by $CS = \{cs_1, cs_2, \ldots, cs_m\}$, where we can locate TLH site and $S = \{s_1, s_2, \ldots, s_n\}$ is the set of all attributes (transformed in benefit attributes) which define CS's selection. For example: "access by public and special transport modes to the candidate site", "security of the candidate site from accidents, theft and vandalism", "connectivity of the location with other modes of transport (highways, railways, seaports, airports, etc.)", "costs in vehicle resources, required products and etc. for the location of a candidate site", "impact of the candidate site location on the environment, such as important objects of critical infrastructure, air pollution and others", "proximity of the candidate site location from the central locations", "proximity of the candidate site location from customers", "availability of raw material and labor resources in the candidate site", "ability to conform to sustainable freight regulations imposed by managers for e.g. restricted delivery hours, special delivery zones", "ability to increase size to accommodate growing customers" and others. Let $W = \{w_1, w_2, \ldots, w_n\}$ be the weights of attributes. For each expert e_k from invited group of experts (service dispatchers and so on) $E = \{e_1, e_2, \ldots, e_t\}$, let α_{ij}^k be the fuzzy rating of his/her evaluation in q-ROFNs for each candidate site $cs_i, (i = 1, \ldots, m)$, with respect to each attribute s_j $(j = 1, \ldots, n)$. For the expert e_k we construct binary fuzzy relation $A_k = \{\alpha_{\text{ij}}^k, i = 1, \ldots, m; j = 1, \ldots, n\}$ decision making matrix, elements of which are represented in q-ROFNs. If some attribute s_j is cost type then we transform experts' evaluations and α_{ij}^k is changed by $(\alpha_{\text{ij}}^k)^c$. Experts' data must be aggregated in etalon decision making matrix - $A = \{\alpha_{\text{ij}},\ i = 1, \ldots, m;\ j = 1, \ldots, n\}$. Our task is to build fuzzy TOPSIS approach, which for each candidate site cs_i $(i = 1, \ldots, m)$, aggregates presented objective and subjective data into scalar values – *candidate site's identification level of the order of establishment* (ILOE) during disaster response. This aggregation can be formally represented as a TOPSIS relative closeness of *candidate site* defined on α_{ij}, $j = 1, \ldots, n$:

$$\begin{aligned} ILOE(\text{cs}_i) &= \text{relative closeness of } \textit{candidate site}(\text{cs}_i) \\ &\equiv \text{TOPSIS aggregation}\,(\alpha_{i1}, \ldots, \alpha_{\text{in}}),\ \ i = 1, \ldots, m. \end{aligned} \tag{9}$$

The proposed scheme of new fuzzy TOPSIS comprises the following steps:

Step 1: *Selection of location attributes.* Involves the selection of location attributes for evaluating potential locations for candidate TLHs. These attributes are obtained from discussion with experts and members of the city transportation group. We use *five attributes* $(n = 5)$ defined above by short names: s_1 = “Accessibility”, s_2 = “Security”, s_3 = “Connectivity to multimodal transport”, s_4 = “Costs”, s_5 = “Proximity to customers”. The fourth attribute is cost type and the others are benefit types. As mentioned above, cost type evaluation data must be transformed in the benefit forms.

Step 2: *Selection of candidate* TLHs *locations.* Involves selection of potential locations for implementing TLHs. The decision makers use their knowledge, prior experience in transportation or other aspects of the geographical area of extreme events and the presence of sustainable freight regulations to identify candidate locations for implementing TLHs. For example, if certain areas are restricted for delivery by municipal administration, then these areas are barred from being considered as potential locations for implementing urban service centers. Ideally, the potential locations are those that cater for the interest of all city stakeholders, which are city residents, logistics operators, municipal administrations, etc.

Step 3: Assignment of ratings to the attributes with respect to the candidate TLHs. Let $A_k = \{\alpha_{\text{ij}}^k \in q - ROFNs,\ i = 1, \ldots, m;\ j = 1, \ldots, n\}$ be the performance ratings of each expert e_k $(k = 1, 2, .., t)$ for each candidate TLH cs_i $(i = 1, 2, .., m)$ with respect to attributes s_j $(j = 1, 2, \ldots, n)$.

Step 4: Computation of the q-ROF decision matrix for the attributes and the candidate TLHs. Let the ratings of all experts be described by positive numbers ω_k, $\omega_k > 0$, $k = 1, \ldots, t$. If ratings of the attributes evaluated by the k-th expert are α_{ij}^k then the aggregated fuzzy ratings (α_{ij}) of candidate TLHs with respect to each attribute are given by q-ROF weighted sum.

$$\alpha'_{ij} = \sum_{k=1}^{t} \oplus_q \alpha_{ij}^k \left(\omega_k / \sum_{l=1}^{t} \omega_l \right). \tag{10}$$

The fuzzy decision matrix $\{\alpha'_{ij}\}$ for the *candidate* TLHs CS and the attributes S is constructed as follows:

$$\begin{array}{c} \\ cs_1 \\ cs_2 \\ \dots \\ cs_m \end{array} \begin{array}{c} \begin{array}{cccc} s_1 & s_2 & \dots & s_n \end{array} \\ \begin{bmatrix} a'_{11} & a'_{12} & \dots & a'_{1n} \\ a'_{21} & a'_{22} & \dots & a'_{2n} \\ \dots & \dots & \dots & \dots \\ a'_{m1} & a'_{m2} & \dots & a'_{mn} \end{bmatrix} \end{array} \tag{11}$$

Step 5: Computation of the q-ROF weighted decision matrix for the attributes and the candidate TLHs. Following to the basic idea of classical TOPSIS, q-rung orthopair fuzzy decision matrix elements $\{\alpha'_{ij}\}$ must be transformed to the weighted q-rung orthopair fuzzy decision matrix elements $\{\alpha_{ij}\}$ by the formula

$$\alpha_{ij} = \left(w_j / \sum_{l=1}^{n} w_l \right) \cdot \alpha'_{ij}. \tag{12}$$

Construct the q-rung fuzzy decision matrix $\{\alpha_{ij}\}$ and calculate Sc and Ac functions values (Definition 2.2) of elements α_{ij}. Calculate total q_0-rung for the elements $\{\alpha_{ij}\}$.

Step 6: *Identification of q-rung orthopair fuzzy PIS and NIS.* TOPSIS approach starts with the definition of the q_0-rung orthopair fuzzy PIS and the q_0-rung orthopair fuzzy NIS. Using formulas (7) of Definition 2.4 the PIS is defined as a q_0-rung orthopair fuzzy set on attributes S: $cs^+ = \{s_j, \alpha_j^+ \equiv \underset{i}{\mathrm{Max}}[(\alpha_{ij})] | j = 1, 2, \dots, n\}$ and the NIS is defined as a q_0-rung orthopair fuzzy set on attributes S: $cs^- = \{s_j, \alpha_j^- \equiv \underset{i}{\mathrm{Min}}[(\alpha_{ij})] | j = 1, 2, \dots, n\}$. In the real MCDM/MADM models PIS and NIS are usually not be feasible alternatives (TLHs). They are extreme hypothetical alternatives.

Step 7. Calculate the distances between the alternative, as candidate TLH *and the* q_0*-rung orthopair fuzzy PIS, as well as* q_0*-rung orthopair fuzzy NIS*, respectively.

Then, we proceed to calculate the distances between each alternative and q_0-rung orthopair fuzzy PIS and NIS. Using equation (8), we define distances between the alternative cs_i and the q_0-rung orthopair fuzzy PIS and NIS, as a weighted sum of distances between extreme and evaluated q_0-ROFNs:

$$\begin{aligned} D(cs_i, sc^+) &= \sum_{j=1}^{n} w_j d_q(\alpha_{ij}, \alpha_j^+) \\ &= 1/2 \cdot \sum_{j=1}^{n} w_j (|(\mu_{\alpha_{ij}})^q - (\mu_{\alpha_j^+})^q| + |(\nu_{\alpha_{ij}})^q - (\nu_{\alpha_j^+})^q|), \\ D(cs_i, sc^-) &= \sum_{j=1}^{n} w_j d_q(\alpha_{ij}, \alpha_j^-) \\ &= 1/2 \cdot \sum_{j=1}^{n} w_j (|(\mu_{\alpha_{ij}})^q - (\mu_{\alpha_j^-})^q| + |(\nu_{\alpha_{ij}})^q - (\nu_{\alpha_j^+})^q|). \end{aligned} \tag{13}$$

Step 8. Calculate the relative closeness or TOPSIS aggregation as a site's identification level of the order of establishment (ILOE*) to identify of the order of establishing temporary logistics hubs during disaster response, for every alternative.*

In general, the bigger $D(cs_i, sc^-)$ and the smaller $D(cs_i, sc^+)$ the better the alternative cs_i to identify of order of its establishment. In the classical TOPSIS method, *authors usually need to calculate the relative closeness (RC) of the alternative cs_i. We define candidate* TLH's *ILOE as* bellow:

$$ILOE(cs_i) \equiv RC(cs_i) = \frac{D(cs_i, cs^-)}{D(cs_i, cs^-) + D(cs_i, cs^+)}, \quad i = 1, \dots, m. \tag{14}$$

4. Multi - objective location set covering problem for TLHs' optimal selection

At the second stage, we are concentrated on the location set covering problem (LSCP) which was proposed by C. Toregas and C. Revell in 1972. This approach seeks a solution for locating the least number of facilities to cover all demand points within the service distance. In some of our works we are focusing on the multi-objective fuzzy set covering problems [24, 30] for extreme conditions. In this section we construct a new fuzzy LSCP model for TLHs' optimal selection planning.

As we discussed in the previous section, constructed Fuzzy TOPSIS technology forms TLH's *identification level of the order of establishment* (ILOE). The ILOE index reflects expert evaluations with respect to the candidate TLH, considering all actual attributes. If $u = \{u_1, u_2, \dots, u_m\}$ is a Boolean decision vector, which defines some selection from candidate TLH's $CS = \{cs_1, cs_2, \dots, cs_m\}$ for facility location, we can *build TLH's total identification level of the order of establishment* as linear sum of $ILOE(cs_j)u_j$ values: As a result, new objective function – *total identification level of the order of establishment* - $\sum_{j=1}^{m} ILOE(cs_j)u_j$ is constructed. Maximizing it will select a group of TLHs with the best *total identification level of the order of establishment* from admissible covering selections. Classical facility location set covering problem tries to *minimize the number of TLHs*, where service facilities can be located - $\sum_{j=1}^{m} u_j$. The problem aims to locate service facilities in minimal travel time from candidate TLHs. Let us demand points covered by the TLHs in distribution networks be denoted by $A = \{a_1, \dots, a_k\}$. The problem aims to locate service facilities in minimal travel time from candidate TLHs. Let experts evaluate movement fuzzy times (evaluated in triangular fuzzy numbers (TFNs) [17] between demand points and candidate TLHs - $\widetilde{t}_{ij}, a_i \in A; cs_j \in$ CS. In extreme environment for emergency planning a radius of service center is defined based not on distance but on maximum allowed time T for movement, since the rapid help and servicing is crucial for demand points in such situations. Respectively, a set of candidate TLHs N_i, covering demand point $a_i \in A$, is defined as $N_i = \{cs_j, cs_j \in CS/E(\widetilde{t}_{ij}) \le T\}, i = 1, \dots, m$, where

$$E(\widetilde{t}_{ij}) = \widetilde{t}^2_{ij} + (\widetilde{t}^3_{ij} - 2\widetilde{t}^2_{ij} + \widetilde{t}^1_{ij})/4 \tag{15}$$

is an expected value [17] of a TFN $\widetilde{t}_{ij} \equiv (\widetilde{t}^1_{ij}, \widetilde{t}^2_{ij}, \widetilde{t}^3_{ij})$. Then we can state bi-objective facility location set covering problem:

$$\min z_1 = \sum_{j=1}^{m} u_j, \quad \max z_2 = \sum_{j=1}^{m} ILOE(cs_j) \cdot u_j$$
$$\sum_{s_j \in N_i} u_j \geq 1 (i = 1, 2, \ldots, k); \quad u_j \in \{0, 1\}, \quad j = 1, 2, \ldots, m. \tag{16}$$

5. Numerical Simulation of Identifying the Order of Establishment and Optimal Selection of TLHs

To facilitate the establishment of TLHs, this stage aims to determine the order in which TLHs should be established. To do so, a fuzzy multi-attribute group decision making approach uses the qualitative attributes selected in this section to evaluate each TLH location alternative.

We illustrate the effectiveness of the constructed new fuzzy TOPSIS model plus TLHs optimal selection planning by the numerical simulation example. Let us consider an emergency management administration of a city in Georgia that wishes to locate some TLHs with respect to timely servicing in simulative disaster. Assume that there are 6 demand points as customers (critical infrastructure objects) and 5 candidate TLHs in the urban area. Let us have 4 experts from Georgian Emergency Management Agency (GEMA) for the evaluation of the travel times and the ranking of candidate facility TLHs. The travel times between demand points and candidate TLHs are evaluated in triangular fuzzy numbers (see Table 1). Let the GEMA standard of location TLHs be that the TLH can reach the area edge within 5 minutes after receiving the dispatched instruction. Therefore, we set covering radius $T = 5$ minutes. Covering sets of candidate sites N_i are defined (omitted here).

Table 1. Fuzzy Travel times $\widetilde{t}_{ij}$ from TLHs to demand points (in minutes).

	a_1	a_2	a_3	a_4	a_5	a_6
cs_1	(3,5,7)	(2,4,6)	(4,6,7)	(4,7,9)	(1,3,5)	(1,3,4)
cs_2	(6,10,14)	(4,9,14)	(2,4,6)	(5,7,10)	(1,4,8)	(1,4,5)
cs_3	(4,8,12)	(4,7,11)	(4,6,9)	(2,4,7)	(4,7,10)	(4,6,8)
cs_4	(4,7,10)	(7,11,15)	(6,9,13)	(4,6,8)	(2,4,6)	(1,3,5)
cs_5	(1,3,5)	(2,4,6)	(1,3,6)	(2,4,7)	(4,6,8)	(5,9,12)

Let experts generate the attributes weights as values of overall importance based on the consensus:

$$w_1 = 0.25; \quad w_2 = 0.15; \quad w_3 = 0.25; \quad w_4 = 0.20; \quad w_5 = 0.15.$$

Each expert e_k $(k = 1, 2, 3)$ presented the ratings r_{ij}^k for each candidate TLH cs_i $(i = 1, \ldots, 5)$, with respect to each attribute s_j $(j = 1, \ldots, 5)$.

Table 2. Appraisal matrix A_1 by expert-1.

	s_1	s_2	s_3	s_4	s_5
cs_1	(0.7, 0.5)	(0.8, 0.3)	(0.7, 0.4)	(0.7, 0.4)	(0.8, 0.4)
cs_2	(0.6, 0.5)	(0.7, 0.4)	(0.4, 0.6)	(0.8, 0.4)	(0.7, 0.4)
cs_3	(0.7, 0.5)	(0.9, 0.5)	(0.9, 0.7)	(0.7, 0.4)	(0.8, 0.5)
cs_4	(0.6, 0.5)	(0.8, 0.4)	(0.8, 0.5)	(0.9, 0.5)	(0.8, 0.5)
cs_5	(0.8, 0.6)	(0.7, 0.4)	(0.9, 0.5)	(0.7, 0.4)	(0.8, 0.6)

Table 3. Appraisal matrix A_2 by expert-2.

	s_1	s_2	s_3	s_4	s_5
cs_1	(0.7, 0.5)	(0.8, 0.4)	(0.6, 0.3)	(0.6, 0.3)	(0.7, 0.4)
cs_2	(0.6, 0.5)	(0.7, 0.3)	(0.7, 0.4)	(0.9, 0.4)	(0.8, 0.4)
cs_3	(0.8, 0.5)	(0.9, 0.5)	(0.6, 0.4)	(0.8, 0.4)	(0.6, 0.2)
cs_4	(0.6, 0.4)	(0.8, 0.3)	(0.9, 0.6)	(0.7, 0.3)	(0.6, 0.2)
cs_5	(0.9, 0.7)	(0.7, 0.4)	(0.9, 0.4)	(0.7, 0.3)	(0.9, 0.6)

Table 4. Appraisal matrix A_3 by expert-3.

	s_1	s_2	s_3	s_4	s_5
cs_1	(0.7, 0.4)	(0.8, 0.3)	(0.7, 0.5)	(0.7, 0.4)	(0.9, 0.5)
cs_2	(0.6, 0.5)	(0.7, 0.4)	(0.5, 0.3)	(0.7, 0.2)	(0.6, 0.3)
cs_3	(0.6, 0.2)	(0.9, 0.6)	(0.7, 0.5)	(0.7, 0.3)	(0.6, 0.3)
cs_4	(0.8, 0.4)	(0.9, 0.4)	(0.8, 0.5)	(0.8, 0.5)	(0.8, 0.3)
cs_5	(0.9, 0.7)	(0.6, 0.3)	(0.9, 0.5)	(0.9, 0.6)	(0.7, 0.4)

Let experts have equal ratings $\{\omega_j = 1/3\}$. Using formula (10) experts' evaluations are aggregated in decision making matrix $\{\alpha_{ij}\}$ (Table 5).

Table 5. Accumulated q-rung orthopair fuzzy decision matrix $\{\alpha_{ij}\}$

	s_1	s_2	s_3	s_4	s_5
cs_1	(0.70,0.46)	(0.80,0.33)	(0.67,0.39)	(0.67,0.36)	(0.83,0.43)
cs_2	(0.60,0.50)	(0.70,0.36)	(0.58,0.42)	(0.83,0.32)	(0.72,0.36)
cs_3	(0.72,0.37)	(0.90,0.53)	(0.79,0.52)	(0.74,0.36)	(0.70,0.31)
cs_4	(0.70,0.43)	(0.84,0.36)	(0.84,0.53)	(0.83,0.42)	(0.76,0.31)
cs_5	(0.88,0.66)	(0.67,0.36)	(0.90,0.46)	(0.80,0.42)	(0.83,0.52)

Using the algorithm from Section 3 (steps 1-8) of new fuzzy TOPSIS, we calculated values of *candidate sites' identification levels of the order of establishment* (ILOE*)*:

$$ILOE(cs_1) = 0.472, \quad ILOE(cs_2) = 0.803, \quad ILOE(cs_3) = 0.441,$$
$$ILOE(cs_4) = 0.455, \quad ILOE(cs_5) = 0.377.$$

Determine the order of establishment of the TLHs finally, this step is to determine the order of establishment of TLHs, and rank the location alternatives based on the crisp values -ILOE. The location alternatives with larger crisp values should be established first, followed by the location alternatives with lower values. The higher crisp value indicates the better performance of alternatives over the selected attributes. Therefore, we obtain a total ordering of THLs:

$$cs_2 \succ cs_1 \succ cs_4 \succ cs_3 \succ cs_5.$$

After these calculations a multi-objective location set covering programming Problem (16) has been constructed:

$$\begin{cases} z_1 = u_1 + u_2 + u_3 + u_4 + u_5 \Rightarrow min, \\ z_2 = 0.472u_1 + 0.803u_2 + 0.441u_3 + 0.455u_4 + 0.377u_5 \Rightarrow \max, \\ u_1 + u_5 \geq 1, \\ u_2 + u_5 \geq 1, \\ u_3 + u_5 \geq 1, \\ u_1 + u_2 + u_4 \geq 1, \\ u_i \in \{0, 1\}, i = 1, 2, 3, 4, 5. \end{cases} \tag{17}$$

Based on the developed software for the problem (17) Pareto solutions [31] are founded. There are:

$$\begin{array}{lllll} \text{a)} & \{cs_1, cs_2\}, & z_1 = 2; & z_2 = 1,18, & cs_1 \succ cs_5; \\ \text{b)} & \{cs_1, cs_2, cs_3\}, & z_1 = 3; & z_2 = 1,716, & cs_2 \succ cs_1 \succ cs_3; \\ \text{c)} & \{cs_1, cs_2, cs_3, cs_4\}, & z_1 = 4; & z_2 = 2,171, & cs_2 \succ cs_1 \succ cs_4 \succ cs_3; \\ \text{d)} & \{cs_1, cs_2, cs_3, cs_4, cs_5\}, & z_1 = 5; & z_2 = 2,548, & cs_2 \succ cs_1 \succ cs_4 \succ cs_3 \succ cs_5. \end{array} \tag{18}$$

It is clear that, increasing of THLs numbers in Pareto solutions gives us better level of the second objective function - *total identification level of the order of establishment.* Also, the orderings of opening THLs in Pareto optimal are given. But the decision on the choice of the THLs as service centers depends on the decision-making person's preferences with respect to risks of administrative or other actions in disaster-stricken zone.

6. Conclusion

Recently, temporary facilities for disaster response have received growing attention from scholars and practitioners alike. However, optimal location selection and ordering are immensely complex due to the lack of information, growing number of humanitarian responders and the need to evaluate subjective attributes during the chaotic disaster response period. This study has presented with two stage methodology. On the first stage, fuzzy multi-attribute group decision making model – new fuzzy TOPSIS model for determining the order of establishment of TLHs is constructed. On the second stage, bi-objective set covering programming problem is created for the optimal selection of TLHs form the ordering TLHs. Interviews with decision makers (general, experts) revealed the differences in their opinion regarding the prominence of different attributes. This difference in decision opinion was also observed when evaluating the performance of selected locations vs, the attributes. Further analysis showed that the order of establishment varies significantly when the locations are evaluated under different scenarios. To illustrate the effectiveness of the constructed new fuzzy two stage methodology, a numerical simulation example is constructed. An emergency management administration of a city in Georgia wishes to locate some TLHs for the timely servicing to demand points in simulation disaster. Four experts from Emergency Management Agency (EMA) of Georgia for the evaluation of the ranking of candidate TLHs were including in the evaluation procedure. This study introduces the concept to the order of establishment of TLHs and demonstrates its importance when resources are limited. It develops and implements a methodology determining the order of establishment of TLHs to support post-disaster decision making. In our future researches different fuzzy FLP mathematical models oriented on real disaster-striking regions' evaluations will be studied.

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