European Journal of Operational Research 250 (2016) 239–250

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Innovative Applications of O.R.

Humanitarian logistics network design under mixed uncertainty

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ARTICLE INFO

Article history:
Received 11 October 2014
Accepted 31 August 2015
Available online 8 September 2015

Keywords:
Humanitarian logistics
Integrated stock prepositioning and relief distribution
Mixed possibilistic-stochastic programming
Differential evolution

ABSTRACT

In this paper, we address a two-echelon humanitarian logistics network design problem involving multiple central warehouses (CWs) and local distribution centers (LDCs) and develop a novel two-stage scenario-based possibilistic-stochastic programming (SBPSP) approach. The research is motivated by the urgent need for designing a relief network in Tehran in preparation for potential earthquakes to cope with the main logistical problems in pre- and post-disaster phases. During the first stage, the locations for CWs and LDCs are determined along with the prepositioned inventory levels for the relief supplies. In this stage, inherent uncertainties in both supply and demand data as well as the availability level of the transportation network's routes after an earthquake are taken into account. In the second stage, a relief distribution plan is developed based on various disaster scenarios aiming to minimize: total distribution time, the maximum weighted distribution time for the critical items, total cost of unused inventories and weighted shortage cost of unmet demands. A tailored differential evolution (DE) algorithm is developed to find good enough feasible solutions within a reasonable CPU time. Computational results using real data reveal promising performance of the proposed SBPSP model in comparison with the existing relief network in Tehran. The paper contributes to the literature on optimization based design of relief networks under mixed possibilistic-stochastic uncertainty and supports informed decision making by local authorities in increasing resilience of urban areas to natural disasters.

1. Introduction

The rate and impact of natural disasters have increased dramatically in the past decades due to population growth, global trend in urbanism, land use and stressing of ecosystems. According to Natural Disaster Database, earthquakes alone have killed more than 700,000 people since 1990 (EM-DAT, 2015). Lack of adequate preparedness in major urban areas has raised likelihood of the deadly and calamitous earthquakes. Destructive effects of disasters, although inevitable, could be mitigated by a proactive approach and the development of appropriate preparedness plans. Responding to a natural disaster within the first 72 hours after its occurrence plays a vital role since communities are not expected to stand on their own for much more than that time (Salmerón & Apte, 2010).

Generally speaking, humanitarian relief chains (HRCs) aim at rapidly providing the emergency supplies for the affected people in order to minimize human suffering and death via efficient and effective allocation of the restricted resources. HRCs are typically configured to address the main humanitarian logistics issues in the preparedness phase of the so-called 'disaster management life cycle'. These issues involve inventory prepositioning network design at pre-disaster phase and relief distribution planning problem at pre-disaster phase, which are addressed in this paper. Interested readers are referred to Balcik and Beamon (2008) for more details about these logistical issues in HRCs.

Coordination of HRCs is complicated and challenging (Balcik, Beamon, Krejci, Muramatsu, & Ramirez, 2010) mainly due to demand uncertainty and the risks associated with trying to deliver relief items efficiently and on time, which are normally exacerbated by the destruction of local infrastructure and resource limitations (Balcik & Beamon, 2008). Dominating characteristics of HRCs including the unpredictability of demand in terms of timing, location, type, and size, and complex coordination due to damages to communication network and other infrastructures differentiate the humanitarian logistics from business logistics. This enforces additional complexity and unique challenges to the management of HRCs (Balcik & Beamon, 2008; Kovacs & Spens, 2007). Nevertheless, despite major *contextual differences* between commercial and humanitarian supply chains, supply chain management (SCM) concepts are at the center of any humanitarian logistical operation (Van Wassenhove, 2006). Hence, designing a HRC needs a SCM approach to coordinate the involved

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http://dx.doi.org/10.1016/j.ejor.2015.08.059

parties, eliminate redundancies, and maximize performances in terms of costs and speed (Tomasini & Van Wassenhove, 2009).

Profit maximization (or cost minimization), which is the main objective in commercial supply chains is replaced by timely and fair provision of aid to beneficiaries in humanitarian operations. In other words, two attitudes (i.e. the egalitarian and utilitarian approaches) should be jointly considered when designing HRCs (De La Torre, Dolinskaya, & Smilowitz, 2012). Egalitarian policies tend to maximize the delivery quantity or speed by considering an equal weight for meeting needs of different target populations. Minimizing the time to deliver goods to beneficiaries is the well-applied egalitarian objective (Duran, Gutierrez, & Keskinocak, 2011). On the other hand, utilitarian objectives tend to focus on needs of the most vulnerable populations and targeting the people with the higher priorities. Minimizing the weighted unmet demand while considering different weights for unmet demands of different demand points, is an example of utilitarian objectives (Salmerón & Apte, 2010).

Uncertainty in the required data is one of the main issues when designing a HRC via optimization models. Particularly, in large-scale emergencies, data may not be available or easy to communicate. As commented by Galindo and Batta (2013, p. 19), "several factors involved in a typical disaster setting introduce uncertainty into parameters such as demands, costs, and travel times. Therefore, it is important to model the uncertainty of such parameters. The use of scenarios might help, but some uncertainty might need to be considered within each scenario, as well".

Generally speaking, randomness and fuzziness are two main sources of uncertainty (Pishvaee & Torabi, 2010; Pishvaee, Torabi, & Razmi, 2012). Randomness stems from the random (chance) nature of data for which, discrete or continuous probability distributions are estimated based on available but sufficient objective/historical data. Stochastic (or robust) programming approaches are usually used to deal with this sort of uncertainty whenever random distributional information is (or is not) available for such input data. Also, using stochastic programming is meaningful only when a certain action can be repeated several times. However, due to special characteristics of disasters, in most cases there is not enough historical/objective data to model uncertain parameters within each scenario as random data. Moreover, there is no repetition in the occurrence of disasters. As such, it is hard or even impossible/meaningless to estimate probabilistic distributions for uncertain parameters in this context. Consequently, in such situations, we are faced with imprecise parameters whose impreciseness arises from the lack of knowledge regarding their exact values, i.e., facing with *epistemic uncertainty* about these data (Kabak & Ülengin, 2011; Pishvaee & Torabi, 2010).

In practice, we often have to rely on judgmental data from decision makers (i.e. field experts) in order to provide reasonable estimations for imprecise parameters. Naturally, these judgmental data are mainly based upon the experts' past experiences and their professional opinions and feelings for which, there might be some (yet insufficient) relevant objective data as well. Accordingly, these parameters have a mixed objective–subjective nature and could be formulated through the possibility theory as a complement to probability theory. Suitable possibility distributions could be adopted for each of these possibilistic data typically in the form of triangular or trapezoidal fuzzy numbers. Moreover, possibilistic programming approaches are usually applied to cope with epistemic uncertainty of imprecise data. It should also be noted that some data might have a fully subjective nature in the form of judgmental data, which are explained by experts. In this case, a fully subjective possibility distribution is adopted for each fully judgmental data based upon the expert's subjective knowledge and feelings. However, in both cases, fuzzy numbers are generally used to formulate the possibility distribution of these imprecise and/or fully subjective data (Torabi & Hassini, 2008).

In the context of HRC design problem, there is an *inherent randomness* about the realized scenario in the post-disaster, which arises from the discrete occurrence probabilities of earthquake scenarios. Also, there is an *inherent impreciseness* (i.e. epistemic uncertainty) in the scenario independent and scenario dependent data. This type of uncertainty includes those data such as demand of each relief item and usable ratio of prepositioned relief items and transportation links in the post-disaster (due to possible damages to storage facilities and transportation routes) under each disaster scenario. For a more detailed description of such parameters, see Section 3. Furthermore, there exists such *impreciseness* about the data at post-disaster, for instance in terms of transportation times in the network's routes under the realized disaster scenario. These data are mainly estimated through a "*needs assessment process*" in the early post-disaster by humanitarian experts who have visited the affected areas based on both available objective evidences and their subjective data according to their past experiences.

Existence of such inherent uncertainties in most of the critical parameters can significantly influence the overall performance of the designed HRC. As such, since we are dealing with a mixture of uncertain data, i.e., imprecise (possibilistic) data within each random disaster scenario in our problem setting, we enhance the classical two-stage stochastic programming framework to cope with the mixture of random and possibilistic data simultaneously. In this way, our methodological contribution can be considered as developing a new method combining traditional stochastic programming with fuzzy numbers to represent different uncertainties involved in the problem (as highlighted by Galindo and Batta (2013)). For this, uncertain disastrous events at post-disaster phase are modeled as stochastic scenarios. The occurrence of each disaster scenario follows a stochastic process where each scenario has its own likelihood. Notably, using stochastic scenarios for modeling probable post-disaster situations is common in HRC design problem (Mete & Zabinsky, 2010; Rawls & Turnquist, 2010). Furthermore, the scenario dependent parameters within each scenario along with scenario independent parameters are formulated as possibilistic distributions in the form of triangular or trapezoidal fuzzy numbers to reflect their impreciseness. The reason for this assumption is that each disaster scenario has its specific conditions and consequences, which are not repetitive. As a result, historical data for such parameters cannot be accumulated. Nevertheless, dealing with such mixed uncertainties will lead to robust solutions by taking into account a portfolio of both random and possibilistic events regarding the various realizations of uncertain data.

This research is motivated by the complex problem of designing a humanitarian relief chain in Tehran. The city is located in an earthquake prone area with three faults running through its populated districts. Therefore, increasing the Tehran's resilience to earthquake is one of the main priorities of local authorities and relief organizations. This involves designing a humanitarian relief network which is addressed in this paper.

In this paper, we propose a hybrid uncertainty programming approach to cope with a range of uncertainties when designing a HRC by incorporating a credibility measure-based possibilistic programming into a scenario-based stochastic programming framework. The proposed approach accounts for imprecise/possibilistic and random data simultaneously by a novel mixed possibilistic-stochastic optimization-based approach. We apply the proposed approach for designing the relief network in Tehran and compare its performance with the pre-planned network. In this way, this research contributes to the literature of optimization-based approaches of HRCs and provides empirical evidence to demonstrate applicability of the proposed approach based on real data for earthquake preparedness in Tehran.

It should be noted that our proposed hybrid uncertainty programming approach is a novel case of the scenario-based stochastic programming (SBSP) framework. In a traditional SBSP framework, model's parameters are formulated by suitable random distributions given the availability of historical data, which is not the case in most disastrous situations. Furthermore, due to the large number of probable scenarios, it is impractical to enumerate and evaluate the entire scenarios. To overcome this limitation regarding dimensionality, scenario generation seems to be essential in order to select a number of sample while effective scenarios. However, in the proposed SBSP approach, the number of disaster scenarios are finite (based upon the seismic studies done in the concerned geographic region), so all of them are taken into account. In such cases, there will be no need for using scenario-generating methodologies to generate sample scenarios. Instead, for each random scenario involving possibilistic (imprecise) parameters, fuzzy chance constrained programming (FCCP) approach is used to convert the respective possibilistic models into their crisp parametric counterparts.

The rest of this paper is organized as follows. The relevant literature is reviewed in the next section. The humanitarian logistics network design model and its corresponding possibilistic-stochastic mathematical formulation are presented in Section 3. Section 4 provides details of the suggested transformation process for converting the original mixed possibilistic-stochastic model into the crisp (deterministic) counterpart and develops a metaheuristic solution algorithm to solve it. The case problem for the design of HRC in Tehran is defined in Section 5 followed by computational results and analysis in Section 6. Finally, the concluding remarks and recommendations are drawn in Section 7.

2. Literature review

For designing HRCs, optimization-based decision models could provide timely and effective solutions for the decision makers. However, analytical methods and optimization-based mathematical models concerning the logistical problems in HRCs under mixed uncertainty are surprisingly scarce in the literature.

Scholars have reviewed the state-of-the-art in the HRCs area from different viewpoints. These include a general review on HRCs (Kovács & Spens, 2007), a comprehensive review on humanitarian logistics (Çelik et al., 2012), a review on coordination issues in HRCs (Balcik et al., 2010), a context analysis of optimization-based models dealing with HRCs (Caunhye, Nie, & Pokharel, 2012) and more recently, a review of recent operations research and management science (OR/MS) research in disaster operations management (Galindo & Batta, 2013). We focus here on optimization-based models addressing the main humanitarian logistics planning issues in the preparedness phase of the so-called 'disaster management life cycle'. Particularly, we limit the literature review to those papers concerning inventory prepositioning or integrated inventory prepositioning and relief distribution planning problem at pre-disaster. In the meantime, we focus on decisions involved without going through their solution procedures as well as those papers addressing uncertainty in their model formulation. Nevertheless, relevant and recent deterministic models (such as Gormez, Koksalan, & Salman, 2011) are also reviewed since they address integrated inventory prepositioning and relief distribution planning.

To the best of our knowledge, Balcik and Beamon (2008) developed the first pre-positioning model by integrating the facility location and inventory decisions into a stochastic programming (SP) framework. Their model is a variant of the maximal covering location model and determines the number and locations of relief distribution centers and the amount of relief supplies to be stocked at each distribution center. Gormez et al. (2011) address a hierarchical facility location problem in which the initial locations of temporary facilities are first selected. Permanent facilities are then located by considering the temporary ones as demand points. Duran et al. (2011) propose an integrated location and inventory planning model to design an international relief pre-positioning network for CARE international which minimizes the expected average response time over all demand points.

Despite the fact that uncertainty is one of the main characteristics of HRCs, there are limited works dealing with this issue while most of them are based on stochastic programming approaches (Galindo & Batta, 2013). In this regard, Mete and Zabinsky (2010) present a two-stage SP model to make joint inventory and distribution decisions for medical supplies. In their model, the location of warehouses and their inventory levels are identified in the first stage. The corresponding distribution plans are then determined in the second stage. Salmerón and Apte (2010) propose a comprehensive two-stage stochastic optimization model with budget allocations in order to minimize the expected number of casualties. The first stage includes decisions regarding the expansion of resources such as warehouses, medical facilities and personnel, ramp spaces and shelters. The second stage deals with decisions concerning the deployment of the allocated resources and contracted transportation assets to rescue critical population, deliver required commodities to stay-back population, and transport the displaced population by the disaster. Rawls and Turnquist (2010) address a two-stage robust stochastic mixed integer program (SMIP) to create an emergency response pre-positioning strategy for hurricanes or other disaster threats. They take into account uncertainty in demands for the stocked supplies as well as uncertainty regarding the availability of the transportation network's routes after a disaster. In another work, Rawls and Turnquist (2011) extend their original model by adding additional service quality constraints to ensure meeting all demands at the pre-specified minimum probability and maximum shipment distance. They use a case study in regards to hurricane threats to illustrate the model and how the additional constraints modify the basic pre-positioning strategy. More recently, Rawls and Turnquist (2012) propose a dynamic allocation model as a two-stage SP to optimize pre-event planning for meeting short-term demands (over approximately the first 72 hours after a disaster) for emergency supplies at shelter locations considering uncertainty of quantities and locations of demand. Döyen, Aras, and Barbarosoğlu (2012) develop a two-echelon two-stage stochastic facility location model to minimize the total cost. Their model aims to find the locations of regional rescue centers (RRCs) and their inventory levels at pre-disaster, the locations of local rescue centers (LRCs) in the post-disaster, the assignment and amount of relief item flows between RRCs and LRCs as well as between the LRCs and demand points, and the amount of unsatisfied demand (shortages) corresponding to each demand point, item, and scenario triplet. Bozorgi-Amiri, Jabalameli, and Mirzapour Al-e-Hashem (2011) present a multi-objective robust stochastic programming model to simultaneously determine the location of relief distribution centers (RDCs) and their inventory quantities for relief items (at the first stage), and the distribution quantities from RDCs to the affected areas (in the second stage). The model aims to minimize the expected total cost, cost variability, and expected penalty for infeasible solutions while maximizing customer satisfaction. The model considers uncertainty in the locations where the demands might arise as well as the possibility that some of the pre-positioned supplies at RDCs or suppliers might partially be destroyed by the disaster (i.e. supply uncertainty). A case study based on a specific disaster scenario in Iran is also provided.

In this paper, we propose a novel decision model, which designs the relief network in two stages. In the first stage, the locations and capacity levels of CWs, the locations of LDCs and the pre-positioned inventory levels of relief supplies at each site are determined. Then, a tentative distribution plan in response to different disaster scenarios is identified in the second stage. Regarding the problem definition and formulation, our contributions (which discriminate the proposed decision model from the current models in the literature when they are collectively taken into account in a mathematical model) are as follows:

- The model takes some real concerns in HRCs into account such as dividing relief items into critical and non-critical items, considering usable ratio of prepositioned inventories under each disaster scenario, disruption of roads, and priority of demand points.
- It considers egalitarian aspects of HRC (by taking total distribution times into account) as well as utilitarian aspects (by means of prioritizing the demand points) simultaneously. These attitudes have often been considered conceptually or quantified separately whereas the proposed model provides a multi-objective mathematical framework for making tradeoff between these two important approaches in humanitarian logistics.
- It develops a two-echelon HRC (including multiple CWs and LDCs) at pre-disaster to optimize cost efficiency and response time effectiveness simultaneously. Furthermore, there is enough flexibility in LDCs' candidate locations so that the model could select the available public facilities such as parks, schools and mosques as LDCs.

Furthermore, from the methodological point of view, our literature review reveals that the existing optimization models for designing relief chains have either been formulated as deterministic (static) or scenario-based stochastic models. Moreover, in all relevant SBSP models, scenario dependent data are considered to be crisp. To the best of our knowledge, there is a gap in the literature taking into account both fuzziness/impreciseness and randomness of the data, which are needed for the design of HRCs. In this paper, we address this gap by developing a novel mixed possibilistic-stochastic model to cope with the two major sources of uncertainty including random disaster scenarios at post-disaster and fuzzy scenario-independent and scenario-dependent parameters in disaster relief operations. The main methodological contribution of the paper is providing an enhanced version of the classical two-stage stochastic programming framework in which, scenario independent and scenario dependent data are treated as imprecise/possibilistic instead of unrealistic crisp data. In this regard, our paper provides a novel approach by incorporating fuzzy numbers into the two-stage stochastic programming for dealing with different uncertainties involved in the problem (i.e. fuzzy and random data). This leads to a more realistic and practical modeling approach in the context of humanitarian logistics. Moreover, within the proposed mixed possibilistic-stochastic model, a new fuzzy ranking method based on the credibility measure is proposed for the defuzzification process to convert the possibilistic chance constraints into their crisp counterparts. Developing a tailored DE algorithm to solve the resultant crisp model to provide good enough solutions in a reasonable amount of time is another methodological contribution of the paper.

The paper also contains a real case study contribution and provides empirical evidence in support of the applicability of the proposed model and solution approach based on the real data regarding earthquake preparedness in Tehran and provides managerial insights for local authorities and relief agencies through comparing the suggested relief network with the current pre-planned network in the city.

3. Problem description

As mentioned above, increasing Tehran's resilience to earthquake by establishing a humanitarian relief network is one of the main priorities of local authorities and relief organizations. Located in an earthquake prone area, Tehran has been destroyed four times between 855AD and 1830. In those incidents, Tehran was a small town and therefore the affected populations were limited. With a population of about 13 million, an earthquake in today's Tehran is likely to result in an unprecedented fatality of above a million which is stated to result the biggest disaster in terms of fatalities and damages in the world (RCS, 2005). Fig. S1 of supplementary material shows the structure of the relief network, which consists of two storage levels, i.e. CWs and LDCs. The CWs with large storage capacities are located in the safe places normally outside of the expected disaster areas. LDCs can be located on the fortified existing public facilities like schools, health centers and mosques which are distributed across the city. The use of LDCs is justifiable as it is not practical to establish a large number of CWs that remain idle until a disaster strikes. Instead, utilizing some existing public facilities could be a better alternative for disaster response purposes (Döyen et al., 2012; Gormez et al., 2011).

Some of the relief items are needed in the early response stage, i.e. the first 24 hours after the disaster occurs. Any delay in sending these items to the affected areas could result in more fatalities. Furthermore, LDCs are closer to demand points while with less capacity compared to CWs. Therefore, assigning their full capacity to the critical items will have higher priority in order to have appropriate response in the early stage of any disaster. Accordingly, we have divided the relief items in two categories: critical items (such as water and medical first aid kits), which could be held in both CWs and LDCs and non-critical but yet important items (such as blankets), which are only held in CWs. Furthermore, population density (number of people per hectare) and structures' destruction ratio of different urban zones are the main factors to prioritize demand points. Further details in this regard are provided in Section 5.

A two-stage possibilistic-stochastic model is proposed to design the relief network by deciding on pre-positioning and distribution of emergency supplies while taking into account pre- and post-disaster events. In the first stage, the best locations for CWs and LDCs are selected among the candidate sites along with the inventory levels for relief supplies in each site. Moreover, the model determines the capacities of the CWs in the first stage. Additionally, alternative distribution plans in response to different disaster scenarios are then identified in the second stage.

In the proposed SBPSP, most of the scenario-independent and dependent parameters are tainted with epistemic uncertainty and therefore considered to be ambiguous or imprecise. These data are represented as possibilistic data in the form of triangular fuzzy numbers. Other assumptions are as follows:

- Most of the relief items are non-perishable. There are some perishable items as well with expiry dates, which are periodically replenished using suitable inventory control policies. The latter group is beyond the scope of our model.
- Replenishment of central warehouses is carried out by national and international suppliers and is beyond the scope of this research.
- Several capacity levels are considered for each candidate CW where appropriate capacity should be determined for each selected CW.
- Vulnerability of storage facilities is taken into account by incorporating different usable inventory ratios for items at each CW/LDS under each scenario. The idea is to capture supply uncertainty as a result of possible destruction of storage sites (partially or completely) during the disaster.
- Vulnerability of transportation network's routes is implicitly modeled through incorporating different transportation times in different disaster scenarios to reflect possible destruction of transportation routes at different levels.

The following notations are used for model formulation where possibilistic/imprecise parameters are represented with tilde ($\sim$) sign.

Indices

l	Index of potential locations for CWs ($l = 1, 2, \ldots, L$)
i	Index of potential points for LDCs ($i = 1, 2, \ldots, I$)
j	Index of affected areas, i.e., demand points ($j = 1, 2, \ldots, J$)
k	Index of relief items ($k \in \mathrm{RI} = \{1, 2, \ldots, K\}$)

CR	Set of critical supplies ($CR = \{1, 2, \ldots, K^c\} \subset RI$)
c	Index for storage capacity levels of CWs ($c = 1, 2, \ldots, C$)
s	Index for probable disaster scenarios ($s \in \delta$)

Parameters

$c\tilde{w}_{lc}$	Establishing cost of lth CW at capacity level c
$c\tilde{d}_i$	Establishing cost of ith LDC
$a\tilde{q}_k$	Unit inventory holding cost of item k
$s\tilde{h}_k^s$	Unit shortage cost of item k under disaster scenario s
$I\tilde{w}_k^s$	Unit inventory cost of unused item k under disaster scenario s at each CW
$I\tilde{d}_k^s$	Unit inventory cost of unused item k under disaster scenario s at each LDC
$t\tilde{w}_{li}^s$	Transportation time between the lth CW and ith LDC to reflect the road and traffic conditions under disaster scenario s
$t\tilde{d}_{ij}^s$	Transportation time between the ith LDC and the jth demand point to reflect the road and traffic conditions under disaster scenario s
$\tilde{d}_{jk}^s$	Demand level for the kth item at the jth demand point under scenario s
w_{jk}^s	Demand priority for the kth item at the jth demand point under scenario s ($\sum_{j\in J}\sum_{k\in RI} w_{jk}^s = 1, \forall s \in \delta$)
$\tilde{\lambda}_{lk}^s$	Usable inventory ratio of the kth item at the lth CW under scenario s
$\tilde{\gamma}_{ik}^s$	Usable inventory ratio of the kth item at the ith LDC under scenario s
$\tilde{b}_c$	Storage capacity of each CW established at capacity level c
$\tilde{e}_i$	Storage capacity of the ith LDC
$\tilde{v}_k$	Required unit storage capacity of the kth item
p^s	Probability of disaster occurrence at scenario $s(\sum_s p^s = 1)$

Decision variable

h_{lc}	1, if the lth candidate CW is opened at capacity level c; 0, otherwise
f_i	1, if the ith candidate LDC is opened; 0, otherwise
q_{lk}	Inventory level of the kth item at the lth CW
r_{ik}	Inventory level of kth item at the ith LDC ($k \in CR$)
uw_{lk}^s	Unused inventory level of the kth item at the lth CW under disaster scenario s
ud_{ik}^s	Unused inventory level of the critical item k at the ith LDC under disaster scenario s
x_{ijk}^s	Amount of the kth critical item to be delivered from the ith LDC to demand point j under disaster scenario s
y_{lijk}^s	Amount of the kth item to be delivered from CW l to demand point j via ith LDC under disaster scenario s
z_{jk}^s	Amount of unfulfilled demand for the kth item in demand point j
T^s	Maximum transportation time under disaster scenario s

Stage 1 – Joint facility location and inventory decisions

The first stage deals with the pre-positioning network design problem taking all possible disaster scenarios at post-disaster into account. The following model is developed to determine the optimal locations for CWs and LDCs, prepositioned inventory level of each relief item at each storage site as well as the optimal capacity level of each CW.

$$\min G = \sum_{l\in L}\sum_{c} c\tilde{w}_{lc}h_{lc} + \sum_{i\in I} c\tilde{d}_i f_i + \sum_{l}\sum_{k\in RI} a\tilde{q}_k q_{lk} + \sum_{i}\sum_{k\in CR} a\tilde{q}_k r_{ik} + E[Q(h, f, r, q, s)] \quad (1)$$

s.t.

$$\sum_{k\in RI} \tilde{v}_k q_{lk} \le \sum_{c} \tilde{b}_c h_{lc}; \quad \forall l \in L \quad (2)$$

$$\sum_{c} h_{lc} \le 1; \quad \forall\, l \in L \quad (3)$$

$$\sum_{k\in CR} \tilde{v}_k r_{ik} \le \tilde{e}_i f_i; \quad \forall\, i \in I \quad (4)$$

$$q_{lk}, r_{ik'} \ge 0; \quad \forall\, l \in L,\ i \in I,\ k \in RI,\ k' \in CR \quad (5)$$

$$h_{lc}, f_i \in \{0, 1\}; \quad \forall\, l \in L,\ i \in I,\ c \in C \quad (6)$$

Objective function (1) minimizes the total operating costs of selected CWs and LDCs, their inventory costs as well as the expected value of the second stage's objective function with respect to the possible disaster scenarios. Since the second stage is a multi-objective model, its expected value is calculated through the weighted augmented ε-constraint method as follows (see Section 4 for more details):

$$Q(h, f, r, q, s) = \theta_1\, \mathrm{obj}_{1s} - \mathrm{range}_{1s} \times \delta \times \left(\theta_2 \frac{\mathrm{sl}_{2s}}{\mathrm{range}_{2s}} + \theta_3 \frac{\mathrm{sl}_{3s}}{\mathrm{range}_{3s}}\right) \quad (7)$$

where θ_1, θ_2 and θ_3 denote the weights of the second stage's objective functions where $\sum_{p=1}^{3}\theta_p = 1$ and δ is a very small number (usually between 10^{-3} and 10^{-6}). Moreover, range_{ps} indicates the range of pth objective function in the second stage under the scenario s. In this way, there will be three objectives under each scenario with different scales. The objective values are normalized by calculating their ideal and nadir solutions and range_{ps} values in order to avoid scaling problem. In addition, sl_{ps} shows the slack variable of pth objective under scenario s. Constraints (2) and (4) enforce restrictions on the available capacity of CWs and LDCs, respectively. Noteworthy, as LDCs do not storage non-critical relief items, constraints (4) show the capacity restriction of LDCs only for critical items. Constraint (3) implies that at most one CW with specified capacity level could be constructed at each candidate site. Finally, constraints (5) and (6) determine the type of decision variables. Notably, there is no weight associated with the CWs and LDCs since there is no priority for selecting the candidate locations in practice. These are potential locations from which, the best locations for establishing CWs and LDCs are determined through the Model (1)–(6) by minimizing the total logistical costs while satisfying capacity and side constraints.

Stage 2 – Relief distribution planning

In the second stage, distribution plans are determined by specifying quantities of the relief items that need to be sent from each CW/LDC to the demand points alongside the unsatisfied demands and unused inventories (as the by-products of the model's solution that enables calculation of the third objective function) under various disaster scenarios. This involves solving the following multi-objective model:

$$\mathrm{obj}_{1s} = \min\left[\sum_{l}\sum_{i}\sum_{j}\sum_{k\in RI}(t\tilde{w}_{li}^s + t\tilde{d}_{ij}^s)y_{lijk}^s + \sum_{i}\sum_{j}\sum_{k\in CR} t\tilde{d}_{ij}^s x_{ijk}^s\right] \quad (8)$$

$$\mathrm{obj}_{2s} = \min T^s \quad (9)$$

$$\mathrm{obj}_{3s} = \min\left[\sum_{j\in J}\sum_{k\in RI} w_{jk}^s s\tilde{h}_k^s z_{jk}^s + \sum_{l}\sum_{k\in RI} I\tilde{w}_k^s uw_{lk}^s + \sum_{i}\sum_{k\in CR} I\tilde{d}_k^s ud_{ik}^s\right] \quad (10)$$

s.t.

$$\sum_{i\in I}\sum_{j\in J} y_{lijk}^s + uw_{lk}^s = \tilde{\lambda}_{lk}^s q_{lk}; \quad \forall\, l \in L,\ k \in RI \quad (11)$$

$$\sum_{j\in J} x_{ijk}^s + ud_{ik}^s = \tilde{\gamma}_{ik}^s r_{ik}; \quad \forall\, i \in I,\ k \in CR \quad (12)$$

$$\sum_{l\in L}\sum_{i\in I} y^s_{lijk} + \sum_{i\in I} x^s_{ijk} = \tilde{d}^s_{jk} - z^s_{jk}; \quad \forall\, j\in J,\ k\in \mathrm{CR} \tag{13}$$

$$\sum_{l\in L}\sum_{i\in I} y^s_{lijk} = \tilde{d}^s_{jk} - z^s_{jk}; \quad \forall\, j\in J,\ k\notin \mathrm{CR} \tag{14}$$

$$\sum_{l\in L}\sum_{j\in J}\sum_{k\in \mathrm{RI}} y^s_{lijk} \le M\cdot f_i; \quad \forall\, i\in I \tag{15}$$

$$T^s \ge \sum_{k\in \mathrm{CR}} \left(w^s_{jk} \sum_{i\in I} t\tilde{d}^s_{ij} x^s_{ijk} \right); \quad \forall\, j\in J \tag{16}$$

$$T^s \ge \sum_{k\in \mathrm{RI}} \left(w^s_{jk} \sum_{l\in L}\sum_{i\in I} \left(t\tilde{w}^s_{li} + t\tilde{d}^s_{ij} \right) y^s_{lijk} \right); \quad \forall\, j\in J \tag{17}$$

$$x^s_{ijk'},\, y^s_{lijk},\, z^s_{jk},\, T^s,\, uw^s_{lk},\, ud^s_{ik'} \ge 0;$$
$$\forall\, l\in L,\ i\in I,\ j\in J,\ k\in \mathrm{RI},\ k'\in \mathrm{CR} \tag{18}$$

Objective function (8) aims to minimize the total distribution times by taking into account distribution quantities. The egalitarian aspect of designed HRC is considered by this objective function. Objective function (9) minimizes the maximum weighted travel time between each pair of CW/LDC and demand point for the critical items. Objective function (10) minimizes the total cost of unused inventories and weighted shortage cost of unmet demands. Objective functions (9) and (10) ensure the utilitarian aspect of designed HRC by using the prioritized demand points. Constraints (11) and (12) ensure that the distributed quantity of each item plus respective unused inventory is equivalent to their corresponding inventory levels at respective CW/LDCs. In this way, the unused inventory level of critical and non-critical items under different disaster scenarios are calculated based on the respective planned inventory levels and distributed amounts.

Constraints (13) and (14) determine the unsatisfied demands for critical and non-critical items, respectively. Furthermore, constraints (15) enforce that the distributed items from CWs to demand points should be transported via the opened LDCs. Moreover, the maximum travel time considering the demand priorities for the items at different demand points is calculated by constraints (16) and (17). Eventually, constraints (18) guarantee non-negativity of variables. Notably, the solution of this model under different scenarios is used to set values of the variables in the first stage.

It should be noted that model (8)–(18) is used to determine a tentative distribution plan at pre-disaster for post-disaster phase. In this model, transportation times between CWs and LDCs and between LDCs and demand points are taken into account to account for distances and road conditions under different disaster scenarios. This model could also be used for post-disaster relief distribution planning by fixing the established storage facilities of the pre-positioning network as input. There are also specific models in the literature for distribution planning at post-disaster with more details such as Najafi, Eshghi, and Dullaert (2013) and Najafi, Eshghi, and De Leeuw (2014). However, the aim of this paper is designing an inventory pre-positioning network at pre-disaster and not developing a detailed distribution plan for post-disaster phase.

4. Solution procedure

The developed scenario-based possibilistic-stochastic framework has several modeling features. It is therefore necessary to propose a step by step solution procedure to deal with the whole problem. In this respect, the multi-objective formulation of the second stage is first converted into an equivalent single objective model through the weighted augmented ε-constraint method (Esmaili, Amjady, & Shayanfar, 2011). The fuzzy chance constrained programming (FCCP) is then applied to reach a minimum confidence level when satisfying the possibilistic chance constraints involving imprecise coefficients (Liu, 2009). The model subsequently is defuzzified (i.e. converted to a crisp counterpart) using a novel credibility measure-based method. The equivalent crisp single objective problem is finally solved using a tailored differential evolution (DE) algorithm (Storn & Price, 1997) to find an efficient (i.e. a compromise or Pareto optimal) solution for the whole problem. This process is iterated in an interactive way with the decision maker to identify alternative compromise solutions. The proposed solution procedure can be summarized as follows:

Step 1: Convert the multi-objective model of the second stage to a single objective problem by using the weighted augmented ε-constraint method.
Step 2: Apply the FCCP approach to the first stage's possibilistic model as well as the resulting single objective possibilistic model of the second stage.
Step 3: Defuzzify the resultant possibilistic single objective model by using the proposed credibility measure-based fuzzy ranking method.
Step 4: Transform the defuzzified two-stage SP model into its crisp equivalent model.
Step 5: Apply the tailored DE algorithm to find an efficient solution for the whole problem.
Step 6: Repeat Steps 1–5 to find the best compromise solution in an interactive way with the decision maker.

The interactive approach in Step 6 allows the decision makers to change control parameters such as the objectives' weight vector, to seek for more preferred compromise solutions in order to satisfy their aspirations (Torabi & Hassini, 2008). Details of the suggested solution procedure are provided in the following subsections. It should also be noted that the time requirements of the whole solution procedure is justifiable, as this is a design problem.

Step 1: Converting the multi-objective model

The ε-constraint method is a common and effective method to solve multi-objective models in search for Pareto optimal solutions. In this method, one of the objectives (often the first one) is optimized while other objectives are added to constraints (Gormez et al., 2011; Mavrotas, 2009). Here, we apply an improved version of this method named the "*weighted augmented ε-constraint method*" (Esmaili et al., 2011) that involves an augmented term in its objective function to ensure yielding an efficient solution for each ε vector (Mavrotas, 2009) along with the priorities of objective functions as well as the ranges of objectives in order to normalize the augmented term to avoid scaling problem. Applying the weighted augmented ε-constraint method to the classic multi-objective problem (i.e., minimizing P objectives simultaneously subject to a feasible decision space X) results in the following model:

$$\min\ \theta_1 f_1(x) - \mathrm{range}_1 \times \delta \times \left(\theta_2 \frac{\mathrm{sl}_2}{\mathrm{range}_2} + \theta_3 \frac{\mathrm{sl}_3}{\mathrm{range}_3} + \cdots + \theta_P \frac{\mathrm{sl}_P}{\mathrm{range}_P} \right)$$
$$\text{s.t.}$$
$$f_p(x) + \mathrm{sl}_p = \varepsilon_p; \quad \forall p = 2, \ldots, P$$
$$x \in X; \quad \mathrm{sl}_p \in R^+ \tag{19}$$

where x is the decision vector, X is the feasible decision space and $f_1(x),\ f_2(x), \ldots,\ f_P(x)$ are the P objectives being minimized. Moreover, δ is a very small number (usually between 10^{-3} and 10^{-6}), and θ_p, range_p and sl_p denote, respectively: the priority (where $\sum_p \theta_p = 1$) and the range of the pth objective function, and the slack variable of respective constraint. The different Pareto optimal solutions could be obtained by changing the ε vector whose possible values should be determined via calculating the range of each constrained objective function. For this, the well-known payoff table is constructed by solving $P - 1$ single objective problem individually. Afterward, the range of each constrained objective (range_p) is calculated and divided into n_p equal intervals and ε_p values are finally calculated as follows (Esmaili et al., 2011).

$$\text{range}_p = f_p^{\max} - f_p^{\min}; \quad \varepsilon_p^l = f_p^{\max} - \frac{\text{range}_p}{n_p} \times l;$$
$$\forall p \neq 1, \quad l = 0, \quad 1, \ldots, q_p - 1 \tag{20}$$

where $f_p^{\max}$ and $f_p^{\min}$ denote the maximum and minimum (i.e. the nadir and ideal) values of objective p, respectively and l is the grid point's number. Therefore, the model (19) is solved for each ε vector leading to a compromise solution for the multi-objective model. Noteworthy, the total number of such models is equal to $\prod_{p=2}^{P}(n_p + 1)$. We use the *early exit* strategy (Mavrotas, 2009) to skip unfeasible models and reduce the computational efforts. For more details on how an efficient solution can be found at each run of the weighted augmented ε-constraint method, interested reader may refer to Esmaili et al. (2011), Mavrotas (2009) and Torabi, Hamedi, and Ashayeri (2013).

In the relief network design problem, objective function (8) is considered as the main objective of the corresponding weighted augmented ε-constraint model while objective functions (9) and (10) are added to the constraints.

Step 2: Applying the FCCP approach

Most of the parameters in the first and second stages are tainted with high degree of epistemic uncertainty that could be effectively formulated by possibility distributions in the form of fuzzy numbers. To this end, the FCCP approach is first applied enabling the decision maker to satisfy the possibilistic chance constraints within selected confidence levels. This provides appropriate reliability for satisfaction of possibilistic chance constraints (Liu, 2009; Pishvaee et al., 2012).

Generally speaking, there are three prominent fuzzy measures in the literature to deal with possibilistic chance constraints (Liu, 2009) by converting the original possibilistic chance constraints into their crisp counterparts. These include possibility, necessity and credibility measures that will be defined in Step 3. The main advantage of these measures is to specify an occurrence degree for each fuzzy (i.e. possibilistic) event in the interval [0, 1] with varying optimistic-pessimistic attitudes. The possibility measure indicates the possibility (i.e. the most optimistic) level of an uncertain event's occurrence (e.g. a possibilistic constraint's satisfaction) that involves possibilistic parameters. In the meantime, the necessity measure shows the corresponding minimum possibility level under the most pessimistic view. Meanwhile, the credibility measure represents the certainty degree of occurring an uncertain event (Liu, 2009).

Unlike the possibility and necessity measures, the credibility measure is self-dual. In other words, a possibilistic event may *fail* even if its possibility degree is one, and *hold* even though its necessity degree is zero. However, a fuzzy event will *hold* if its credibility degree is one, and *fail* if its credibility degree is zero (Liu, 2009). For this reason, we use the credibility measure to convert the possibilistic chance constraints into their crisp counterparts in our formulation as it is closer to certainty and its results would be more reliable than those related to the possibility and necessity measures.

The standard FCCP model can be expressed as follows (Liu, 2009):

$$\begin{aligned} &\min\ \bar{f} \\ &\quad \text{s.t.} \\ &\qquad \text{Cr}\big(f(x,\xi) \le \bar{f}\big) \ge \beta \\ &\qquad \text{Cr}\big(g_j(x,\xi) \le 0\big) \ge \alpha_j; \quad \forall j \end{aligned} \tag{21}$$

where ξ is a vector of fuzzy coefficients, f and g_j denote the possibilistic objective function and the jth possibilistic constraint, respectively. Furthermore, β and α_j are the minimum confidence levels for satisfaction of the possibilistic objective function and jth possibilistic constraint, respectively. It should be noted that using the credibility measure ensures the satisfaction of possibilistic objective function and constrains at the certainty level of at least β and α_j. In this way, the FCCP approach is applied to the possibilistic equations. For example, Eq. (2) can be converted as follows:

$$\text{Cr}\left(\sum_{k \in \text{RI}} \tilde{v}_k q_{lk} - \sum_{c} \tilde{b}_c h_{lc} \le 0\right) \ge \beta \tag{22}$$

Step 3: The proposed defuzzification method

Fuzzy ranking methods are used to deal with soft constraints involving imprecise (i.e. possibilistic) parameters on left- and/or right-hand sides. There are various fuzzy ranking methods, which are mostly based on possibility and necessity measures (e.g. Mahmodi-Nejad & Mashinchi, 2011). Nevertheless, we propose a new fuzzy ranking method based on the credibility measure to deal with the possibilistic chance constraints in the formulated model. Noteworthy, as mentioned in Step 2, possibility and necessity measures demonstrate extremely optimistic and pessimistic attitudes, respectively, while the credibility measure implies a moderate and more practical attitude. In this way, the credibility measure could be considered as the most reliable measure leading to satisfy the possibilistic chance constraints at the most reliable way (Pishvaee et al., 2012).

Let $\tilde{a}$ and $\tilde{b}$ are two possibilistic parameters formulated by the following triangular possibilistic distributions (i.e. fuzzy numbers):

$$\tilde{a} = \text{TFN}(a_1, a_2, a_3), \quad \tilde{b} = \text{TFN}(b_1, b_2, b_3) \tag{23}$$

The possibility degree to which $\tilde{a} \le \tilde{b}$ could be calculated as follows (Das, Maity, & Maiti, 2007; Liu & Iwamura, 1998):

$$\text{Pos}\big(\tilde{a} \le \tilde{b}\big) = \begin{cases} 0 & a_1 \ge b_3 \\ \dfrac{b_3 - a_1}{b_3 - b_2 + a_2 - a_1} & a_2 \ge b_2,\ a_1 \le b_3 \\ 1 & a_2 \le b_2 \end{cases} \tag{24}$$

Also, the following relations hold between the possibility, necessity and credibility measures (Liu, 2009):

$$\text{Nec}\big(\tilde{a} \le \tilde{b}\big) = 1 - \text{Pos}\big(\tilde{a} \ge \tilde{b}\big) \tag{25}$$

$$\text{Cr}\big(\tilde{a} \le \tilde{b}\big) = \frac{1}{2}\Big(\text{Pos}\big(\tilde{a} \le \tilde{b}\big) + \text{Nec}\big(\tilde{a} \le \tilde{b}\big)\Big) \tag{26}$$

Now, the fuzzy ranking formulation (24) can be reformulated as follows in terms of the credibility measure:

$$\text{Cr}\big(\tilde{a} \le \tilde{b}\big) = \begin{cases} 0 & a_1 \ge b_3 \\ \dfrac{b_3 - a_1}{2(b_3 - b_2 + a_2 - a_1)} & a_2 \ge b_2,\ a_1 \le b_3 \\ \dfrac{a_3 - b_1 + 2b_2 - 2a_2}{2(b_2 - b_1 + a_3 - a_2)} & a_2 \le b_2,\ a_3 \ge b_1 \\ 1 & a_3 \le b_1 \end{cases} \tag{27}$$

Consequently, $\tilde{a}$ will be less than or equal to $\tilde{b}$ at least at the confidence level α whenever:

$$\text{Cr}\big(\tilde{a} \le \tilde{b}\big) \ge \alpha \equiv \begin{cases} \dfrac{b_3 - a_1}{2(b_3 - b_2 + a_2 - a_1)} \ge \alpha; & \text{if } 0 \le \alpha \le 0.5 \\ \dfrac{a_3 - b_1 + 2b_2 - 2a_2}{2(b_2 - b_1 + a_3 - a_2)} \ge \alpha; & \text{if } 0.5 \le \alpha \le 1 \end{cases} \tag{28}$$

Specifically, for symmetric triangular fuzzy numbers, the crisp equivalent of fuzzy inequality $\text{Cr}(\tilde{a} \le \tilde{b}) \ge \alpha$ can be simplified as follows:

$$a^c + (2\alpha - 1)w_a \le b^c + (1 - 2\alpha)w_b; \qquad \forall \alpha \tag{29}$$

where a^c and w_a denote the center and range of the symmetric fuzzy number $\tilde{a}$, respectively.

Step 4: Treatment of randomness

There are various methods in order to treat the random data in two/multi-stage SP models such as L-shaped method (Rawls & Turnquist, 2010), Benders decomposition (Escudero, Garín, Merino, & Pérez, 2009), and scenario decomposition (Ruszczynski & Shapiro, 2003). Interested reader may refer to Birge and Louveaux (1997) for more details. For problems with finite number of scenarios like the one addressed in this paper, the deterministic single stage method is more popular. More explanations of this method are provided in the supplementary material.

In this way, the equivalent crisp model of the HRC problem is reformulated as follows, where all fuzzy parameters are simply considered as symmetric triangular fuzzy numbers with 10 percent spread in both sides (i.e., $\tilde{a} = \langle a^C,\ 0.1\,a^C\rangle \equiv \mathrm{TFN}(0.9a^C, a^C, 1.1a^C)$):

$$\min G = \frac{g - g_{\min}}{g_{\max} - g_{\min}} + \sum_{s\in S} P_s\left(\theta_1 \frac{\mathrm{obj}_{1s} - \mathrm{obj}_{1s_{\min}}}{\mathrm{range}_{1s}} - \delta \times \left(\theta_2 \frac{\mathrm{sl}_{2s}}{\mathrm{range}_{2s}} + \theta_3 \frac{\mathrm{sl}_{3s}}{\mathrm{range}_{3s}}\right)\right) \tag{30}$$

s.t.

$$g = \sum_{l\in L}\sum_{c} cw_{lc}^C(0.9+0.2\,\alpha)h_{lc} + \sum_{i\in I} cd_i^C(0.9+0.2\,\alpha)f_i + \sum_{l}\sum_{k\in \mathrm{RI}} aq_k^C(0.9+0.2\,\alpha)q_{lk} + \sum_{i}\sum_{k\in \mathrm{CR}} aq_k^C(0.9+0.2\,\alpha)r_{ik} \tag{31}$$

$$\sum_{k\in \mathrm{RI}} v_k^C(0.9+0.2\,\alpha)q_{lk} \le \sum_{c} b_c^C(1.1-0.2\alpha)h_{lc};\quad \forall l \in L \tag{32}$$

$$T^s + \mathrm{sl}_{2s} = \varepsilon_2^s;\quad \forall\, s \in S \tag{33}$$

$$\sum_{j\in J}\sum_{k\in \mathrm{RI}} w_{jk}^s sh_k^{s\,C}(0.9+0.2\,\alpha)\, z_{jk}^s + \sum_{l}\sum_{k\in \mathrm{RI}} Iw_k^{s\,C}(0.9+0.2\,\alpha)\, uw_{lk}^s + \sum_{i}\sum_{k\in \mathrm{CR}} Id_k^{s\,C}(0.9+0.2\,\alpha)\, ud_{ik}^s + \mathrm{sl}_{3s} = \varepsilon_3^s;\qquad \forall\, s \in S \tag{34}$$

$$\begin{cases} \sum_{i\in I}\sum_{j\in J} y_{l\,ij\,k}^s + uw_{lk}^s \le \lambda_{lk}^{s\,C}(1.1-0.1\,\alpha)q_{lk}; \\ \sum_{i\in I}\sum_{j\in J} y_{l\,ij\,k}^s + uw_{lk}^s \ge \lambda_{lk}^{s\,C}(0.9+0.1\,\alpha)q_{lk}; \end{cases} \quad \forall\, l \in L, k \in \mathrm{RI} \tag{35}$$

$$\begin{cases} \sum_{l\in L}\sum_{i\in I} y_{lij\,k}^s + \sum_{i\in I} x_{i\,j\,k}^s \le\ d_{j\,k}^{s\,C}(1.1-0.1\,\alpha) - z_{jk}^s; \\ \sum_{l\in L}\sum_{i\in I} y_{lij\,k}^s + \sum_{i\in I} x_{i\,j\,k}^s \ge\ d_{j\,k}^{s\,C}(0.9+0.1\,\alpha) - z_{jk}^s; \end{cases} \quad \forall\, j \in J, k \in \mathrm{CR} \tag{36}$$

$$T^s \ge \sum_{k\in \mathrm{CR}}\left(w_{jk}^s \sum_{i\in I} td_{i\,j}^{s\,C}(0.9+0.2\,\alpha)x_{i\,j\,k}^s\right);\quad \forall j \in J \tag{37}$$

Constraints (4), (12), (14) and (17) are reformulated in a similar way to (32), (35), (36) and (37), respectively. Incidentally, constraints (3), (5), (6), (15) and (18) are remained unchanged. It should be noted that to avoid scaling problem, the first stage's objective function has been normalized, where $g_{\min}$ and $g_{\max}$ represent the minimum and maximum values associated with g respectively. Readers may see, for example, Tzeng, Cheng, and Huang (2007) for similar normalization. Moreover, the second stage's objectives were normalized based on ε-constraint method by dividing the slacks to the objectives' ranges.

Solving the above mixed integer linear programming (MILP) model for a given epsilon vector will lead to an efficient solution for the original multi-objective model. The most preferred compromise solution could be finally found in an interactive way in which, the decision maker can change the epsilon vector as well as other control parameters such as the objectives' weights.

Step 5: Tailored differential evolution

The equivalent MILP model (i.e. the crisp counterpart) of the HRC problem could be very large especially for real cases. As a result, application of exact optimization using commercial optimization solvers like CPLEX in GAMS is not practical. We therefore develop a tailored differential evolution (DE) algorithm to find good-enough and feasible solutions within a reasonable CPU time. DE is a population-based metaheuristic, which has advantages over other metaheuristics such as simulated annealing (SA) and genetic algorithm (GA) because of its simple structure, easy implementation, speed and robustness (Storn & Price, 1997). It starts with generating a set of random and diverse solution vectors based on lower and upper bounds of the variables. New (trial) solutions are then generated by applying mutation and crossover operators to the initial solutions. The next generation of solutions is constructed by comparing the objective value of each trial solution vector and the target vector. This procedure is repeated for a predetermined number of generations ($G_{\max}$) or stopped if the current solutions cannot be improved anymore (Das & Suganthan, 2011). The key parameters, i.e., the population size (*NP*), mutation factor (*F*) and crossover rate (*CrossRate*), should be set for a given problem by trial and error. The details of tailored DE algorithm as well as the details of whole solution procedure (Steps 1–4) are provided in the supplementary material.

5. The case description

In this section, we provide details of the case study for the design of HRC in Tehran to improve the existing relief network aiming at better response to a potential earthquake. The network will be established with 22 LDCs and six CWs by considering all candidate locations for CWs and LDCs. We refer to this as *pre-planned network* hereafter. The main sources of data for the case study are the reports by Japan International Cooperation Agency (JICA, 2000) and Tehran Red Crescent Society (RCS, 2005). These include earthquake scenarios, destruction ratios of structures and facilities in different regions under each scenario, which are used for calculating usable inventory ratios, relief items needed by each family after disaster, and cost of setting up LDCs and CWs. The rest of data such as total demand in each district and transportation times were calculated based on these data. Tehran involves three main faults: Mosha, North of Tehran (NTF) and Rey. The movement of each active fault may result in an earthquake. Moreover, the concurrent movement of two or more faults causes more catastrophic earthquakes. Here, this is called the floating (hybrid) model (JICA, 2000). Probability of an earthquake in each fault is estimated for days and nights separately since the disruption level of an earthquake scenario depends on the occurrence time. Table S1 of supplementary material presents the probability of each disaster scenario.

Tehran consists of 22 districts, which are considered as the demand points for detailed planning. Priorities of the demand points were calculated according to their potential seismic hazards and damages (including average seismic intensity, residential destruction ratio and death ratio), and social conditions (including population density, open space per person and narrow road ratio), which are extracted from JICA (2000). This information is summarized in Table S2 of supplementary material. Damage ratio is the structures' destruction ratio, which affects prioritizing the demand points. The demand points with higher average seismic intensity, residential destruction

Table 1
Comparison of published relevant papers with the proposed one.

Paper	Covered phases	Geographical scope	# of inventory echelons	Decisions involved			Concerned objective functions				Type of uncertainty
				Location\allocation	Inventory planning	Distribution	Total cost	Total distance\time	Maximum dist.\time	Unsatisfied demand	
Balcik and Beamon (2008)	P, IR	Dom	1	L	√	√				√	SBSP
Mete and Zabinsky (2010)	P, IR	Loc	1	L	√	√	√	√		√	SBSP
Rawls and Turnquist (2010)	P, IR	Loc	1	L	√	√	√				SBSP
Rawls and Turnquist (2011; 2012)	P, IR	Loc	1	L,A	√	√	√				SBSP
Salmerón and Apte (2010)	P, IR	Dom	1	L,A	√	√				√	SBSP
Gormez et al. (2011)	P	Dom, Loc	2	L				√	√		-
Bozorgi-Amiri et al. (2011)	P, IR	Dom, Loc	1	L	√	√	√			√	SBSP
Duran et al. (2011)	P, IR	Int	1	L	√	√		√			SBSP
Döyen et al. (2012)	P, IR	Dom, Loc	2	L,A	√	√	√				SBSP
The proposed model	P, IR	Dom, Loc	2	L	√	√	√	√	√	√	SBPSP

Covered phases: P: Preparedness, IR: immediate response.
Geographical scope: Int: International (NGOs), Dom: National or domestic, Loc: Local.
Decisions involved: L: Locating warehouses, A: Allocation of demand points to the distribution centers.
Type of uncertainty: SP: Stochastic programming, SBSP: Scenario-based SP, SBPSP: Scenario-based possibilistic-stochastic programming.

ratio, death ratio and population density and also those with lower open space per person and narrow road ratio are more vulnerable and henceforth have higher priority under a utilitarian approach. The demand points are prioritized using these six criteria. For further description, these six criteria were classified and ranked from 1 to 5, where 1 indicates the lowest priority and 5 the highest. For example, the population density (in terms of number of people per hectare) in each district is in the range of 10–360 persons per hectare. This range has been classified into the five categories (JICA, 2000). The first ranked category includes the range of 10–80 and the fifth ranked category includes the range of 290–360. Afterward, the final priorities are estimated by the summation of ranking of all criteria for each district. Notably, these priorities are assumed to be equal for the relief items as well as for the occurrence time (day or night).

It is assumed that each LDC is capable to fulfill the requirements of 5000 families (of five as average family size). Only one LDC could be established in each district. As mentioned before, there are 22 districts in Tehran and the set I involves 22 candidate locations. These were selected from among the current public facilities across the city, which could be fortified to act as LDCs. Moreover, six candidate locations around Tehran (Fig. S2 of supplementary material) are nominated for establishing required CWs. The capacity of the CWs could be selected at three levels: 50, 100 and 150 thousands families (RCS, 2005). Notably, the inventory constraints (i.e., Eqs. (3) and (5)) are replaced by supply limitations on the number of items based on the available information. Furthermore, the average operating costs for setting up each LDC and CW are estimated at 1.2 and 12.5 billion Iranian Rials, respectively (RCS, 2005). The other cost rates, i.e., the holding, shortage and unused inventory costs have been estimated by experts in Tehran municipality in the scale of 10^4, 10^6 and 10^6 Rials, respectively.

Demands are estimated based on the population and number of affected people in each district under each disaster scenario detailed in JICA (2000) as well as 55 relief items needed by each family as defined in RCS (2005) (see Table S3 of supplementary material). Relief items include basic needs of families at post-disaster including items such as water, some food, health items (such as drugs, bandages, first aid kits), cloths, shelter (such as tents and blankets) and relief equipment. It is noteworthy that all imprecise parameters of the developed model are considered as symmetric triangular fuzzy numbers in the case study. For the fuzzy parameters, the provided data represent the central values of the associated fuzzy numbers. The fuzzy numbers were then constructed by considering 10 percent spread in both sides of the central values.

Transportation times are estimated by taking into account the distance between the districts as well as estimated destruction ratios. Destruction ratios for the pre-positioned items stored at each LDC and CW are also considered by capturing the subjective likelihood of destruction of the warehouses during earthquake. The destruction ratios are respectively estimated as 0.1 and 0.01 of destruction ratios of the most resistant buildings in respective districts according to JICA (2000).

6. Computational results

6.1. Implementation

The solution procedure was firstly validated on a set of five small-sized test problems involving three CWs, two LDCs and five demand points with one relief item under two disaster scenarios. Each problem instance was solved by GAMS software and the proposed DE algorithm. The DE algorithm was coded in Matlab (R2010a) and executed on a PC with Intel Dual Core CPU, 2.53 gigahertz with 2.87 gigabyte of RAM. Furthermore, based on the results of initial tests by trial and error, parameters of the DE algorithm, i.e., *CrossRate*, *F*, *NP* and *Gmax* were set to 0.9, 0.8, 100 and 600, respectively. It is noteworthy that higher *NP* values might result in better solutions but due to memory limitation, we kept *NP* at 100 and increased the number of generations (*Gmax*) to improve quality of results. The results were compared to the results of DE algorithm in order to validate the solution procedure (Table 2). The calculated gaps between the results of GAMS and DE demonstrate the validity of proposed solution procedure and its applicability for solving the real-sized problems.

6.2. Results and analysis

The resultant MILP model for the case of Tehran consists of 32,067 constraints, 8 continuous variables, 291,940 integer variables and 68 binary variables. In order to alleviate the computational complexity, which is partly due to the consideration of three capacity levels (50, 100 and 150 thousands families) for each CW, the binary variables associated with CWs' locations (h_{lc} variables) were converted to integers by considering each CW with capacity of 50,000 units as one CW. For example, yielding value 2 for such a variable means establishing a CW with capacity of 100,000 units at respective location. An efficient solution is found in each run of the DE algorithm, which takes more than 4 hours. This computational time is not unusual given the high complexity of the model and very large size of the case study.

Fig. S3 of supplementary material shows the results of sensitivity analysis, which is carried out for the weight vector $(\theta_1, \theta_2, \theta_3)$ by considering the objective function (8) as the main objective of the corresponding weighted augmented ε-constraint model. It is worth noting that the objective (8) was the most important objective based upon the experts' opinions, which reflects their inclination toward egalitarian rather than utilitarian aspects of the designed HRC. Noteworthy, in our numerical tests, the objectives' weight vector was set to (0.4, 0.3, 0.3).

Table 2
Comparison of GAMS and DE solutions on small-sized instances.

Problem instance	Solution method	Operating and storing costs (Rials)	Expected total transportation time (in minutes)	Expected maximum transportation time (in minutes)	Expected unused and shortage cost (Rials)
1	GAMS	52,046	5408.968	4337.732	254,740
	DE	53,838	5457.72	4389.62	263,718
2	GAMS	36,146	2647.88	782.28	346,836
	DE	36,410	2742	787.32	355,078
3	GAMS	50,880	4795.44	2029.476	263,392
	DE	51,288	4978.51	2074	267,797
4	GAMS	36,040	1993.86	608.44	348,192
	DE	36,418	2027.04	616.31	349,930
5	GAMS	51,622	3760.032	1429.728	255,416
	DE	53,491	3803.24	1482.28	255,577
Average gap (percent)		1.93	2.21	1.77	1.63

As can be seen in the figure, the vertical axis shows the expected scaled value of the objectives in the second stage. To calculate these values, the objective function values under each scenario in the second stage were first normalized by means of their maximum and minimum values (similar to Eq. (30) in Step 4 of solution procedure). Then, the expected values of these normalized objectives were calculated by considering the probability of disaster scenarios. Hence, for each weight vector shown in the horizontal axis, a scaled value is computed for each objective of the second stage. The results show that the impact of weights on the objectives' values is negligible. This could be justified based on the objectives' normalization to avoid scaling problem, which might be occurred when solving the multi-objective problem in the second stage. In other words, as the objectives were scaled between one and zero, changing the weights would affect the objectives' values very slightly. This provides high flexibility for decision makers to conveniently incorporate their preferred weights.

As mentioned before, experts' opinions regarding the weights of objectives indicate an egalitarian tendency (as the objective (8) is weighted higher than objectives (9) and (10)). To investigate the effect of these weights on final results while changing the main objective of the corresponding weighted augmented ε-constraint model, two additional sensitivity analyses are also carried out. In these analyses, the utilitarian objectives (9) and (10) are considered respectively as the main objective of the corresponding weighted augmented ε-constraint model. In this way, one can see if there is any difference in the final results when changing the experts' attitudes from the egalitarian to utilitarian approach. The results demonstrate that the impact of weight vector on the objectives' values when looking at each case separately is still negligible (see Figs. S4 and S5 of supplementary material). Furthermore, by reviewing the numerical results shown in these figures, it can be realized that the gap of shortage and unused cost between S3–S4, S3–S5 and S4–S5 is about 7 percent, 11 percent and 3 percent respectively. The gap of other objectives (i.e. total transportation time and maximum transportation time) is between 1 and 4 percent as well. These results reveal that changing the main objective within the utilitarian approach does not affect the results considerably as the differences between Figs. S4 and S5 are negligible. However, switching from the egalitarian to utilitarian approach (especially when comparing Fig. S3 with Fig. S5) causes somehow considerable differences especially on the cost objective (10). In other words, the shortage and unused cost (objective (10)) decreases between 7 and 11 percent when switching from the egalitarian objective (8) to a utilitarian objective while the other objectives were increased about 1–4 percent.

Another sensitivity analysis was conducted for the confidence level (α) whose results are presented in Table 3. The solution of the (non-fuzzy) Two-Stage Stochastic Programming (TSSP) model is also presented in the last row of Table 3 for which, the center of each fuzzy parameter is used instead of the respective fuzzy parameter. In this manner, we could compare the numerical results of the proposed SBPSP model with those of TSSP model to compare performance of the SBPSP model with the non-fuzzy TSSP model.

As can be seen in Table 3, when the confidence level increases, all objective values are escalated considerably. This observation demonstrates sensitivity of the SBPSP to the confidence level. The results also reveal that the SBPSP model outperforms the TSSP model in terms of all objective functions, which indicate flexibility of the proposed SBPSP model. Such flexibility is achieved by incorporating the fuzzy numbers into the classic TSSP framework, which lead to account for possible changes in scenario-dependent and -independent imprecise parameters. It means that several solutions for the problem under consideration could be achieved since a wider range of each imprecise parameter is taken into consideration through a fuzzy variable compared to its deterministic case, which considers only one value for each parameter. Accounting for such epistemic uncertainty in parameters would lead to the robustness of final solutions as the possible fluctuations in scenario-dependent and -independent parameters are suitably taken into account during the solution process. This is of particular importance for strategic decisions like designing HRCs which cannot be changed easily during a long-term planning horizon. In this way, considering fuzzy parameters (which alleviate the challenge of exact estimation of data) and soft constraints (which are presented by incorporating a minimum confidence level (α) on possibilistic constraints) provide these aspects of flexibility. This is one of the main advantages of fuzzy modeling as it has already been mentioned in other works as well (see, for instance, Vafa Arani & Torabi, 2015).

It should also be noted that increasing the confidence level leads to more restrictions on the fuzzy equations. In other words, it advocates a more pessimistic approach, which can be observed in the increasing trend of objective values in Table 3. Incidentally, this is one of the parameters that could be adjusted by the decision makers based on their preference as the satisfaction level of fuzzy constraints. Additionally, SBPSP enables decision makers to reach a balance between the two conflicting criteria in an interactive way. In other words, they can improve the objective function value or to improve degree of feasibility for the soft constraints. It should be noted that considering the expected intervals for model's parameters and taking the two sources of uncertainty into account, it is expected that our model eventually leads to robust solutions and therefore, sensitivity analysis is deemed unnecessary here.

Additionally, the three prominent fuzzy measures (i.e. the necessity, possibility and credibility measures) are separately applied for deffuzifying FCCP model at the confidence level (α) 0.8. The results are then compared to demonstrate the effect of each fuzzy measure on the final solutions (see Table S4 of supplementary material). As

Table 3
Sensitivity analysis for confidence level (α).

Model	Operating and storing costs (Rials)	Expected total transportation time (minute)	Expected maximum transportation time (minute)	Expected unused and shortage cost (Rials)
SBPSP model with $\alpha = 0.5$	3.4143E+11	7.2004E+08	2.0096E+06	7.9557E+11
SBPSP model with $\alpha = 0.8$	3.4622E+11	7.6602E+08	2.0167E+06	8.7009E+11
SBPSP model with $\alpha = 1$	3.5307E+11	7.8740E+08	2.0203E+06	9.2135E+11
TSSP model	4.4602E+11	8.1737E+08	2.1782E+06	9.3748E+11

Table 4
Comparative results.

	Operating and storing costs (Rials)	Expected total transportation time (minute)	Expected maximum transportation time (minute)	Expected unused and shortage cost (Rials)
Proposed SBPSP (with $\alpha = 0.8$)	3.4622E+11	7.6602E+08	2.0167E+06	8.7009E+11
Pre-planned network	7.2096E+11	2.3801E+09	6.8856E+06	8.3598E+12

it was expected, the necessity and possibility measures result in the most pessimistic and optimistic values, respectively. Meanwhile, the credibility measure results in moderate and the most reliable values. These results show the higher reliability of the credibility measure compared to the possibility and necessity measures.

Finally, Table 4 presents the comparative results between the proposed relief network and the pre-planned relief network in terms of objective values. As mentioned before, the pre-planned relief network includes all six candidate CWs in six potential locations with the minimum capacity level as well as all 22 candidate LDCs. In other words, the locations and inventory levels of CWs and LDCs were fixed in the pre-planned network and the second stage decisions were obtained accordingly.

Comparative study of the resultant efficient solutions (which are not presented here due to space limitation) reveal that establishing all candidate LDCs and CWs, specifically two CWs with the medium capacity and the rest at the minimum level are essential. Most of the efficient solutions suggest establishing a CW with medium capacity near Tehran International Airport (CW 6 in Fig. S2 of supplementary material). It could be justified since the airport is located at the South of Tehran in a location that enables it to support the southern areas whose population densities and expected destruction ratios are high. The other CW with medium capacity is located in the West of Tehran (CW 3 in Fig. S2 of supplementary material) or East of the city (CW 5 in Fig. S2 of supplementary material). Another important observation is that even constructing all candidate CWs and LDCs is not sufficient to fulfill all demands. This observation emphasizes the need to increase the number of candidate locations. It should be noted that the preparedness plans are provided just for the first 72 hours after an earthquake; extra demands will need to be satisfied via the national and international organizations. The results demonstrate that the proposed relief network increases the proportion of satisfied demand by more than 25 percent from 0.276 in the pre-planned network to 0.347 in the proposed network.

Since the operating costs are assumed to be equal for all CWs as well as all LDCs, the population density and closeness of each district to the candidate LDCs and CWs play a vital role in the selected location and capacity levels of CWs. Moreover, each CW and LDC in the pre-planned network is dedicated to special and specified amount of demand. The proposed SBPSP accounts for the density of population in each district as a significant factor in determining inventory quantities.

In summary, the experimental results demonstrate that the proposed relief network outperforms the pre-planned network with respect to a range of monetary and time-based criteria. In the meantime, the proposed SBPSP model offers enough flexibility when designing a relief network by changing the control parameters (e.g., the objectives' weight vector and confidence level of soft constraints). It also provides a set of compromise solutions that are highly important due to the strategic nature of the problem when preparing the final preparedness plan. This flexibility is achieved by considering the input data as fuzzy numbers and satisfying the constraints in a soft manner by incorporating minimum confidence levels for satisfaction level of uncertain constraints through a credibility measure-based FCCP approach. Such flexibility has also decreased the infeasibility and inconsistency issues, which are the main disadvantages of deterministic models. Furthermore, the challenge of exactly matching supply and demand data when designing a HRC is alleviated by means of the proposed SBPSP model. Based on the aforementioned facts, it can be concluded that the proposed SBPSP model is a reliable and practical decision support tool for designing efficient and effective humanitarian relief networks.

7. Conclusion

Unpredictability and the uncertain nature of disasters are the key challenges of designing HRCs. In addition, the need to find a balance between main performance criteria such as response time, demand satisfaction level and cost efficiency complicates further the design of HRCs. In this paper, a novel SBPSP model is proposed for humanitarian logistics network design problem, which is capable of coping with the uncertainty and multiple objectives of the decision problem, simultaneously. The uncertainties are treated by taking into account inherent fuzziness and randomness in the available data. The model deals with preparedness and response planning and takes into account distribution planning of relief items during stock prepositioning.

The proposed SBPSP model is converted into an equivalent crisp model by using a mixed possibilistic-stochastic approach. A tailored interactive DE algorithm is proposed in which, the decision maker is able to input her/his preferences like confidence level to find alternative solutions. The proposed model is applied to the design of relief network in Tehran and the outcome is compared with the existing pre-planned network. The results indicate robustness of the SBPSP model and superiority of the resulting solution compared to the existing network.

The current research can be extended in a number of directions. A hierarchical planning framework could be considered in HRC design problem to decrease computational complexity by solving the stock pre-positioning and relief distribution sub-problems sequentially. In addition, the proposed model could be extended, for instance by considering capacity constraints on transportation routes, determining suitable inventory control policies for perishable relief items and allowing possible lateral transshipments between various LDCs to decrease the unmet demands. Obtaining optimal solutions even for medium-sized problem instances needs huge computational storage capacities and times while it is almost impossible in large-sized problems. Therefore, developing other meta-heuristic methods to improve time-efficiency of the proposed solution approach could be considered as a suitable avenue for further research.

Acknowledgments

This research was supported in part by University of Tehran under the research grant no. 8109920/1/12 and Economic and Social Research Council (ESRC) of UK under grant no. RES-067-27-0027. The authors appreciate the constructive comments made by the anonymous reviewers, which helped to improve presentation of the paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2015.08.059.

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