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Robust humanitarian relief logistics network planning

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A B S T R A C T

In recent years, death toll of natural and man-made disasters has increased at an appalling rate. Thus, disaster management and especially efficient management of humanitarian relief efforts seem to be essential. This paper presents a bi-objective mixed-integer mathematical model for Humanitarian Relief Logistics (HRL) operations planning, as an important part of the humanitarian relief efforts. This model determines optimal policies including location of warehouses, quantity of emergency relief items that should be held at each warehouse, and distribution plan to provide an emergency response pre-positioning strategy for disasters by considering two objectives. The first one minimizes the average response time and the second one minimizes the total operational cost including the fixed cost of establishing warehouses, the holding cost of unused supplies and the penalty cost of unsatisfied demand. The survival of pre-positioned supplies, demand amount and routes condition following an event are considered under uncertainty in the model solved by a robust scenario-based approach. The robust approach is applied to reduce the effects of fluctuations of the uncertain parameters with regards to all the possible future scenarios. The research demonstrates the applicability and usefulness of the proposed model on a case study on earthquake preparation in the Seattle area in USA. In addition, the work applies the Reservation Level Tchebycheff Procedure (RLTP) method to solve the bi-objective model in an interactive way with decision maker. This work provides practitioners, specifically planning teams, with a new approach to assist with disaster preparedness and to improve their logistics decisions.

1. Introduction

In recent years, death toll of natural and man-made disasters has increased at an alarming rate; today about 70,000 people die and 200 million people are affected by disasters each year (Duran *et al.*, 2011). For instance, 222,570 individuals lost their lives in Haiti Earthquake in 2010 [http://reliefweb.int/sites/reliefweb.int/files/resources/2012.07.05.ADSR_2011.pdf, accessed 18 July 2013]. Thus, the necessity for appropriate measures to control such terrible disasters is extremely understood.

Altay and Green III (2006) surveyed the literature to address potential research directions in disaster operations. They identified that one of the main activities in disaster areas is the HRL operations,

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which can be defined as "the process of planning, implementing and controlling the effective, cost-efficient flow and storage of goods and materials as well as related information, from the point of origin to the point of consumption for the purpose of meeting the end beneficiary's requirements" (Thomas and Mizushima, 2005).

Trestrail *et al.* (2009) recommended the pre-positioning to promote the efficiency of HRL operations. Indeed, relief organizations can efficiently respond to emergency conditions if they develop a pre-positioned network, in which the quantity of supplies and location of warehouses are certain (Duran *et al.*, 2011). Caunhye *et al.* (2012) characterized the problem of location with relief distribution and stock pre-positioning (LRDSP). In this category, Balcik and Beaman (2008) proposed a maximal-covering model that determines the number and locations of the distribution centers and the quantity of stocked supplies at each distribution center. They considered uncertainty in the location of disasters and the demand by a scenario-based approach, assuming that multiple scenarios would not occur simultaneously. Rawls and Turquist (2008) proposed a two-stage stochastic mixed-integer programming model that combines facility location, decision on stocking levels for emergency supplies with uncertainty about demand, survival of pre-positioned stocks and transportation network condition, following the occurrence of an event. Mete and Zabinsky (2010) developed a two-stage stochastic programming model for a preparedness phase and determined warehouses locations and their inventory levels. The objective functions to be minimized were the transportation duration and the unsatisfied demands. Duran *et al.* (2011) proposed a mixed-integer programming model that estimates the frequency, location and magnitude of potential demand based on historical data. The model optimizes the location of warehouses and inventory allocation under considered constraints. It also minimizes the average response time as an objective function. Tofighi *et al.* (2011) presented a two-stage fuzzy stochastic model for pre-positioning and distribution of emergency supplies in the humanitarian relief chain. In the first stage, locations for warehouses among the potential candidates are determined along with their inventory levels. In the second stage, a distribution policy in response to different disaster scenarios is identified.

Although there are some studies in the literature that propose multi-objective models for HRL problem (Lin *et al.*, 2011; Bozorgi-Amiri *et al.*, 2013; Najafi *et al.*, 2013; Zhang and Jiang, 2013), multi-objective optimization that considers simultaneously time and cost as objectives in the specific category of LRDSP in HRL has never been addressed.

This paper presents a novel bi-objective mixed-integer programming model for a HRL problem in the specific category of LRDSP. This model considers two objectives: (1) minimizing the average response time, and (2) minimizing the total cost (i.e., the establishing warehouses, unused supplies, and unsatisfied demand costs). In fact, in an emergency situation, responsiveness appears to be a major concern (Caunhye *et al.*, 2012). Hence, we minimize the average response time (objective 1) and the penalty of unmet demands (i.e., objective 2) in order to consider the responsiveness issue. Funding after the occurrence of a disaster is much easier to obtain than for a pre-disaster management (Murray, 2005). Therefore, the model minimizes the total cost of preparedness and the other operational costs in objective function 2.

In disaster areas, people expect to see fairness in distributing relief items among demand points. If the minimum fairness level is not satisfied, it may lead to a social disaster in addition to the humanitarian crisis. To avoid this problem, we propose a fairness level constraint as a novelty in the LRDSP category. This constraint ensures distribution of relief items among demand points in a fair way.

Kovács and Spens (2007) described the specific characteristics of HRL. HRL problems inherently have uncertainty in their input data (Tofighi *et al.*, 2011). Balcik and Beamon (2008) described the main characteristics of the relief chain network design, such as uncertainty and unpredictability of demand (in terms of type, size, location and timing) and lack of resources and infrastructure (e.g., money, transportation capacity and supply). Hence, HRL problem similar to many real-world planning problems involve noisy, incomplete or inaccurate data. In the literature, different approaches have been applied to deal with different forms of uncertainty. Mathematical programming and stochastic approaches were applied to formulate uncertainty in HRL problem (Rawls & Turnquist, 2010; Mete and Zabinsky, 2010). Another approach to incorporate uncertainty in HRL models is fuzzy approach (Tofighi *et al.*, 2011). Recently, robust optimization model, strong technique to contrast uncertainty, was applied to deal with uncertainty in the disaster area (Lin *et al.*, 2011; Bozorgi-Amiri *et al.*, 2013; Najafi *et al.*, 2013; Zhang & Jiang, 2013). Robust optimization can be very efficient and capable since generation of the proper and stable solutions for any possible occurrences of uncertain parameters (Mulvey *et al.*, 1995).

Mulvey *et al.* (1995) introduced the concept of robust optimization in operation research. They presented a robust counterpart approach with a nonlinear regularization function penalizing the constraint violations and uncertainties are considered via a set of discrete scenarios. Robust optimization has resulted in series of solutions that are progressively less sensitive to realizations of the data in a set of scenarios. The optimal solution of robust optimization model is robust with regards to optimality if it remains ‘close’ to the optimal if input data change: this is termed solution robustness. The solution is also robust with regards to feasibility if it remains ‘almost’ feasible for low level changes in the input data: this is called model robustness. The traditional stochastic linear program fails to determine a robust solution despite the presence of a weak robust point (Bai *et al.*, 1997). Bai *et al.* (1997) examined features of risk-averse utility functions in robust optimization. They inferred that a concave utility function should be incorporated in a model whenever the decision maker tends to be a risk averse. Ben-Tal and Nemirovski (1998) presented a robust optimization approach to formulate continuous uncertain parameters. Ben-Tal and Nemirovski (2002), Ben-Tal and Nemirovski (2002) and Ben-Tal *et al.* (2002) proposed robust theory of linear, quadratic and conic quadratic problems. Their approaches are applied in engineering and design problems at high level. Bertsimas and Sim (2002) and Bertsimas and Thiele (2003) developed robust optimization methods for discrete optimization in continuous spaces.

Bozorgi *et al.* (2013) presented a multi-objective robust stochastic programming model for disaster relief logistics. They considered demands, supplies, cost of procurement and transportation as the uncertain parameters. Moreover, they attempted to minimize the expected value and the variance of the total cost of the relief chain, and the maximum shortages in the affected areas. Najafi *et al.* (2013) proposed a multi-objective, multi-mode, multi-commodity, and multi-period stochastic model to manage the logistics of both commodities and injured people in the earthquake response. They applied a robust approach to make sure that the distribution plan performs well under the various conditions that can follow a disaster. Zhang and Jiang (2013) presented a bi-objective robust program to design a cost-responsiveness efficient emergency medical services (EMS) system under uncertainty. They developed a robust counterpart approach to cope with the uncertain parameters in the EMS system. Eventually, the present paper develops a robust stochastic multi objective mathematical model for HRL problem in LRDSP category that two significant differences in comparison with similar works (Bozorgi-Amiri *et al.*, 2013; Zhang and Jiang, 2013); (1) considering time in the mathematical model, and (2) introducing fairness level constraint for considering fair factor.

Another contribution of this paper is the development of an efficient Reservation Level Tchebycheff Procedure (RLTP) that is applied to solve the presented bi-objective model in an interactive way with decision maker. Table 1 shows the differences of the present work with the other works in the LRDSP category in detail.

Table 1
Objectives, constraints, and other decisions for location models with relief distribution and stock pre-positioning

References	Objectives		Constraints			Other decisions
	Cost	Time	Capacity	Requirements and bounds	Other	
Chang *et al.*, 2007	Transportation, facility opening, equipment rental, penalties, shipping distance of rescue equipment	-	Facility	-	Prioritized facility allocation	Storage, shortage/surplus, rescue center grouping
Duran *et al.*, 2011	-	Response	-	Number of facilities, total inventory	-	-
Iakovou *et al.*, 1997	Facility opening, operations, transportation	-	Facility	Critical time to meet demand	-	-
McCall , 2006	Transportation, shortages		Facility	Number of kits to pre-position	Investment budget	Unmet demand
Mete & Zabinsky, 2010	Warehouse operations, unmet demand	Transportation	Vehicle	Inventory shortage upper bound threshold	-	Unmet demand
Psaraftis *et al.*, 1986	Facility opening, stock acquisition, transportation, operations, unmet demand, delay	-	-	-	-	Unmet demand
Rawls & Turnquist, 2010	Facility opening, transportation, unmet demand, holding	-	Facility, link	-	-	-
Rawls & Turnquist, 2011	Facility opening, transportation, unmet demand, holding	-	Facility, link	Average distance limit, Demand requirements for scenarios	-	-
Rawls & Turnquist, 2012	Facility opening, transportation, unmet demand, holding	-	Facility, link, dispatch	-	-	-
Wilhelm & Srinivasa, 1996	Facility opening and expansion, stock acquisition, operations		Facility	Time-phased cleanup requirement	-	Capacity addition
Bozorgi-Amiri et al., 2013	Facility opening, Warehouse operations, unmet demand, holding	-	Facility	-	-	Unmet demand, Unused stock
Zhang & Jiang, 2013	Facility opening, Warehouse operations, unmet demand, transportation	-	-	-	-	Vehicle
Present Work	Warehouse Facility opening, operations, unmet demand, holding	Response	Facility, link	Fairness level upper bound threshold	Investment budget	Unmet demand, Unused stock, Vehicle

The structure of the paper is as follows. In Section 2, the HRL problem is described and a bi-objective mathematical model is developed. The robust model is described in Section 3. In Section 4, the RLTP method is elaborated. In Section 5, a case study is described and its computational results are presented in Section 6. Finally, Section 7 presents the conclusion and future research directions.

2. Problem description and formulation

There are different scenarios based on location and time of the occurrence of a disaster. The relief organization should be prepared to face these probable different situations, and manage them in an effective way. Therefore, the organization needs pre-planning on required equipment and supplies. Medical supplies are one of the required items. Hence, it is necessary to prepare the required amount of these medical items, put in the suitable locations, and pre-position required equipment (i.e. vehicles) in order to distribute the supplies according to the specific and important purposes deemed important by the humanitarian intervention (i.e., minimum response time and operating cost). A bi-objective mathematical model is presented for this relief items storage and distribution problem at a city area. The model determines optimal pre-disaster policy including location of warehouses, quantity of the relief items that should be held at each warehouse and, distribution plan of the relief items to demand points. In addition, the model considers inherent uncertainty of the HRL problem (i.e., about roads, demands, relief items, transportation time and priority) about the occurrence of the different disaster scenarios based on time and location. The following assumptions are considered for the problem:

2.1. Assumption

- Number and location of candidate warehouses are known.

- Location and number of potential demand points are known.
- Demand of points can be satisfied by any warehouse.
- Multiple relief items are considered.
- Amount and priority of relief items in each demand point are uncertain following an event.
- Amount of survival relief items in each warehouse are uncertain following an event.
- Just one specific route exists between each demand point and warehouse.
- Unusable routes are uncertain following an event.

2.2. Indices

i index of possible pre-positioning warehouses (i=1,2,…,I),
j index of demand points (j=1,2,…,J),
k index of relief items (k=1,2,…,K),
s index of scenarios (s=1,2,…,S).

2.3. Parameters

p_s probability of occurrence of scenario s,
t_{ijks} time to satisfy demand for item type k from warehouse i to demand point j in scenario s (hours),
F_i fixed cost of establishing warehouse i ($),
ρ_{iks} proportion of stocked material of relief item type k at location i that remains usable in scenario$s$; ($0\le \rho_{iks} \le 1$),
τ_{jks} penalty cost of each unsatisfied item type k for demand point j in scenario s,
γ_{ik} capacity of warehouse i for item type k,
h_k additional unit holding cost of item type k,
d_{jks} amount of demand for demand point j for item type k in scenario s,
B maximum of available budget for establishing warehouses,
ξ_k maximum amount available of each relief item type,
ψ maximum of tolerable proportion of shortage at each demand point,
Cap capacity of each vehicle,
Δ_{pq} maximum acceptable difference of fairness level between two demand points p and q ($p \neq q$).

2.4. Decision variables

x_{ijks} quantity of item type k sent to demand point j from warehouse i in scenario s,
q_{ik} amount of item type k pre-positioned at warehouse i,
z_{iks} amount of item type $k$in warehouse i that is not used in scenario s,
w_{jks} shortage of item type k at demand point j in scenario$s$,
φ_j amount of weighted shortage at demand point j,
n_{is} number of vehicle pre-positioned at warehouse i in scenario$s$,
y_i 1 if the warehouse i is opened, 0; otherwise.

Based on the above-mentioned definitions, we develop the following bi-objective mixed-integer mathematical model.

2.5. Mathematical model

$$\min z_1 = \sum_{s=1}^{S} p_s \sum_{j=1}^{J} \left[\frac{\sum_{i=1}^{I} \sum_{k=1}^{K} x_{ijks} t_{ijks}}{\sum_{k=1}^{K} d_{jks}} \right] \tag{1}$$

$$\min z_2 = \sum_{i=1}^{I} F_i y_i + \sum_{s=1}^{S} p_s \left(\sum_{i=1}^{I}\sum_{k=1}^{K} h_k z_{iks} + \sum_{j=1}^{J}\sum_{k=1}^{K} \tau_{jks} w_{jks} \right) \tag{2}$$

subject to

$$d_{jks} = w_{jks} + \sum_{i=1}^{I} x_{ijks} \quad \forall j \in \{1,...,J\}, k \in \{1,...,K\}, s \in \{1,...,S\} \tag{3}$$

$$q_{ik} \le y_i \gamma_{ik} \quad \forall i \in \{1,...,I\}, k \in \{1,...,K\} \tag{4}$$

$$\sum_{i=1}^{I} q_{ik} \le \xi_k \quad \forall k \in \{1,...,K\} \tag{5}$$

$$\sum_{j=1}^{J} x_{ijks} + z_{iks} = \rho_{iks} q_{ik} \quad \forall i \in \{1,...,I\}, k \in \{1,...,K\}, s \in \{1,...,S\} \tag{6}$$

$$x_{ijks} \le M t_{ijks} \quad \forall i \in \{1,...,I\}, j \in \{1,...,J\}, k \in \{1,...,K\}, s \in \{1,...,S\} \tag{7}$$

$$\sum_{i=1}^{I} F_i y_i \le B \tag{8}$$

$$-\Delta_{pq} \le \varphi_p - \varphi_q \le \Delta_{pq} \quad \forall p,q \in \{1,...,J\} \quad p \ne q \tag{9}$$

$$\varphi_j = \sum_{s=1}^{S}\sum_{k=1}^{K} \tau_{jks} w_{jks} \quad \forall j \in \{1,...,J\} \tag{10}$$

$$\sum_{k=1}^{K} w_{jks} \le \psi \sum_{k=1}^{K} d_{jks} \quad \forall j \in \{1,...,J\}, s \in \{1,...,S\} \tag{11}$$

$$\frac{1}{Cap} \sum_{j=1}^{J}\sum_{k=1}^{K} x_{ijks} = n_{is} \quad \forall i \in \{1,...,I\}, s \in \{1,...,S\} \tag{12}$$

$$x_{ijks} \ge 0 \quad \forall i \in \{1,...,I\}, j \in \{1,...,J\}, k \in \{1,...,K\}, s \in \{1,...,S\} \tag{13}$$

$$q_{ik} \ge 0 \quad \forall i \in \{1,...,I\}, k \in \{1,...,K\} \tag{14}$$

$$z_{iks} \ge 0 \quad \forall i \in \{1,...,I\}, k \in \{1,...,K\}, s \in \{1,...,S\} \tag{15}$$

$$w_{jks} \ge 0 \quad \forall j \in \{1,...,J\}, k \in \{1,...,K\}, s \in \{1,...,S\} \tag{16}$$

$$n_{is} \ge 0 \quad \forall i \in \{1,...,I\}, s \in \{1,...,S\} \tag{17}$$

$$y_i \in \{0,1\} \quad \forall i \in \{1,...,I\} \tag{18}$$

The objective function (1) minimizes the average weighted response time over all scenarios. The weights correspond to the proportions of demand satisfied from the warehouses. The response time is the time required for shipment to reach the demand location, which depends on the distance and duration time between the warehouse and the demand point. This objective tries to select the warehouses that satisfy the demand points with the least time. The objective function (2) minimizes the total cost consisting of the fixed cost of establishing warehouses (i.e., term 1), additional holding cost for unused supplies (i.e., term 2), and total penalty cost of unsatisfied demand that considers the priority of each demand point for each supply implicitly by value of penalties (i.e., term 3).

Funding is easy to obtain after disaster has occurred because of governmental and international subsidies; however, obtaining funding for pre-disaster is considerably more difficult (Murray *et al.*, 2005). Therefore, the model tries to minimize the total cost of preparedness and the other operational cost by objective function (2) (i.e., term 1 and 2).

Eq. (3) limits the sum of supplies delivered to each demand point and the amount of unsatisfied demand to the demand amount of each demand point. Eq. (4) shows that, if warehouse i is opened, the corresponding amount of items type k cannot exceed the warehouse capacity. The limitation on the availability of the relief items for storage in the warehouses is shown in Eq. (5). Eq. (6) ensures that the sum of the shipped supplies and unused supplies are equal to the amount of usable stocked material. Eq. (7) ensures that the shipped supplies are sent through usable routes (if a route is not usable, its duration time is considered as zero). Eq. (8) shows the budget limitation for establishing each warehouse. All operational costs such as personnel, maintenance, etc. are considered in the parameter F_i for each warehouse i.

To ensure a consequent fairness level, the constraint (9) is introduced for the first time in the LRDSP problem category. Therefore, for each demand point, we define total penalty cost of unmet demands (10) as a fairness level. Penalty cost of each unmet demand k is considered based on its priority in demand point j following an event s (τ_{jks}). Constraint (9) ensures that difference of weighted unsatisfied demands between two demand points does not exceed a maximum considered amount of fairness level defined by experts. On the other hand, this constraint ensures the distribution of relief items among demand points in a fairly way.

The model considers the maximum amount of unmet demands for each demand point by equation (11). The number of vehicles to be prepositioned in each warehouse following each scenario is determined by Eq. (12). Eqs.s (13-17) are non-negativity limitations, and Eq. (18) indicates that opening a warehouse location is a binary decision.

3. Robust optimization model for the humanitarian relief logistics network planning problem

3.1 Framework of robust optimization model

Robust optimization is used to obtain a set of solutions that are robust against the fluctuation of parameters or input data in future. Mulvey *et al.* (1995) presented the robust optimization approach. The framework of robust optimization approach is briefly described. The primary optimization LP model is as follows:

$$\text{Min } \; c^T x + d^T y \tag{19}$$

subject to

$$Ax = b, \tag{20}$$

$$Bx + Cy = e, \tag{21}$$

$$x, y \geq 0, \tag{22}$$

where y is the vector of control variables and x is the vector of decision variables. Constraint (20) is the structural constraint whose coefficients are free of noise and deterministic. Constraint (21) is the control constraint whose coefficients are subject to noise and random. Uncertain parameters are modeled with a set of scenarios $\Omega = \{1,2,,\ldots,s\}$ in robust optimization. So that, the set $\{B_s, C_s, e_s, d_s\}$ is the set of uncertain parameters under each scenario s and $\sum_s p_s = 1$ where p_s shows the probability of scenario s. The scenario based robust optimization approach is described as follow:

$$\min \; c^T x + \sum_{s \in \Omega} d_s^T + y_s + \lambda\sigma(y_1, y_2, \ldots, y_s) + \omega\rho(\delta_1, \delta_2, \ldots, \delta_s)$$

subject to

$$Ax = b,$$

$$B_s x + C_s y + \delta_s = e_s$$

$$x, y_s \geq 0 \qquad s \in \Omega$$

The purpose of this model is to balance the tradeoff between model robustness and solution robustness. The optimal solution of this model will be robust regarding optimality if it remains ‘close’ to optimality for any realization of each scenario $s \in \Omega$ (solution robustness). The solution is also robust regarding feasibility if it remains 'almost' feasible for any realization scenario s (model robustness). The parameter δ_s is defined for model robustness, which measures the infeasibility allowed in the control constraints under scenario s. For more details on solution robustness and model robustness features, readers are referred to Yu and Li (2000). Mulvey *et al.* (1995) proposed a quadratic form and Yu and Li (2000) developed an absolute form for the term $\sigma(y_1, y_2, \dots, y_s)$.

3.2. Proposed robust optimization model

Robust optimization approach proposed by Mulvey *et al.* (1995) and Yu and Li (2000) is applied to formulate the two-stage humanitarian relief logistics network planning problem. In this paper, an absolute penalized form is used for obtaining the solution robustness measure in objective function. The developed robust optimization model for the mentioned problem can be stated by:

$$\min z_1 = \sum_{s=1}^{S} p_s \sum_{j=1}^{J} \left[\frac{\sum_{i=1}^{I}\sum_{k=1}^{K} x_{ijks} t_{ijks}}{\sum_{k=1}^{K} d_{jks}} \right] + \lambda_1 \sum_{s=1}^{S} p_s \left(\left(\sum_{j=1}^{J} \left[\frac{\sum_{i=1}^{I}\sum_{k=1}^{K} x_{ijks} t_{ijks}}{\sum_{k=1}^{K} d_{jks}} \right] - \sum_{s'}^{S} p_{s'} \sum_{j=1}^{J} \left[\frac{\sum_{i=1}^{I}\sum_{k=1}^{K} x_{ijks'} t_{ijks'}}{\sum_{k=1}^{K} d_{jks'}} \right] \right) + 2\theta_{1s} \right) \tag{24}$$

$$\min z_2 = \sum_{i=1}^{I} F_i y_i + \sum_{s=1}^{S} p_s \left(\sum_{i=1}^{I}\sum_{k=1}^{K} h_k z_{iks} + \sum_{j=1}^{J}\sum_{k=1}^{K} \tau_{jks} w_{jks} \right) +$$
$$\lambda_2 \sum_{s=1}^{S} p_s \left[\left(\left(\sum_{i=1}^{I}\sum_{k=1}^{K} h_k z_{iks} + \sum_{j=1}^{J}\sum_{k=1}^{K} \tau_{jks} w_{jks} \right) - \sum_{s'=1}^{S} p_{s'} \left(\sum_{i=1}^{I}\sum_{k=1}^{K} h_k z_{iks'} + \sum_{j=1}^{J}\sum_{k=1}^{K} \tau_{jks'} w_{jks'} \right) \right) + 2\theta_{2s} \right] + \omega \sum_{s=1}^{S} p_s \delta_s \tag{25}$$

subject to

$$d_{jks} - w_{jks} - \sum_{i=1}^{I} x_{ijks} = \delta_s \quad \forall\, j \in \{1,\dots,J\}, k \in \{1,\dots,K\}, s \in \{1,\dots,S\} \tag{26}$$

$$\left(\sum_{j=1}^{J} \left[\frac{\sum_{i=1}^{I}\sum_{k=1}^{K} x_{ijks} t_{ijks}}{\sum_{k=1}^{K} d_{jks}} \right] - \sum_{s'}^{S} p_{s'} \sum_{j=1}^{J} \left[\frac{\sum_{i=1}^{I}\sum_{k=1}^{K} x_{ijks'} t_{ijks'}}{\sum_{k=1}^{K} d_{jks'}} \right] \right) + 2\theta_{1s} \geq 0 \tag{27}$$

$$\left(\left(\sum_{i=1}^{I}\sum_{k=1}^{K} h_k z_{iks} + \sum_{j=1}^{J}\sum_{k=1}^{K} \tau_{jks} w_{jks} \right) - \sum_{s'=1}^{S} p_{s'} \left(\sum_{i=1}^{I}\sum_{k=1}^{K} h_k z_{iks'} + \sum_{j=1}^{J}\sum_{k=1}^{K} \tau_{jks} w_{jks'} \right) \right) + 2\theta_{2s} \geq 0 \tag{28}$$

$$\theta_{1s}, \theta_{2s}, \delta_s \geq 0 \tag{29}$$

with constraints (4)–(18).

The first and second terms in objective function (24, 25) are the mean value, and the second and third terms in them are variance of total costs respectively, and they measure solution robustness. The forth term in Eq. (25) measures the model robustness with regards to infeasibility associated with control constraints Eq. (26) under scenario *s*.

4. Solution methodology

4.1. Selection of appropriate multi-objective programming technique

HRL decisions are linked to the choice of the decision maker (DM). A DM in charge of the network design project is considered in this work. Hence, the bi-objective mixed integer model should be solved to obtain non-dominated solutions, considering the DM's preferences. Considering the bi-objective mathematical model and the necessity of interactivity relation with the DM in the decision-making process (selecting the efficient policies or non-dominated solutions), interactive multi-objective programming (MOP) methods are adapted to the problem (Alves & Climaco, 2004).

It is difficult for the DM to specify accurately her/his preference on the goals in multi-objective optimization problems (Huang *et al.*, 2005). The most effective methods are interactive procedures that generally include solution generation and evaluation phases (Gardiner & Steuer, 1994). There are three important points in the interactive MOP methods (Sun *et al.*, 1996): (1) how to imply preference information from the DM over a set of candidate solutions, (2) how to systematically represent the DM's preference, and (3) how to use the DM's preference to improve solutions. Some of the popular interactive MOP methods include the Geoffrion-Dyer-Feinberg procedure, the Tchebycheff method, the visual interactive approach, STEM, the Zionts-Wallenius method, the reference point method (Gardiner and Steuer, 1994), the interactive FFANN procedure (Sun *et al.*, 1996; Sun *et al.*, 2000) and the IIMOM procedure (Huang *et al.*, 2005). Furthermore, different scalarization methods are possible (Alves & Climaco, 2004; Sun *et al.*, 2000). Some of these methods are not suitable for the real life problems when they consider discrete decision variables (hence, the set of non-dominated solutions is not convex), while they are adapted only for problems with a convex feasible region and concave objective functions (Demirtas & Üstün, 2008). In addition, the methods that use weighted sums of the objective functions cannot provide every non-dominated solution of the problems (Demirtas & Üstün, 2008). Non-dominated solutions contain both supported and unsupported non-dominated solutions. Unsupported solutions are dominated by convex combination of other non-dominated solutions. Tchebycheff metric-based programs provide a way of reaching every non-dominated solution in comparison with weighted sums programs (Demirtas & Üstün, 2008). A Tchebycheff scalarizing program is one of the reference point approaches that compute the weak non-dominated solution closest to a reference point (e.g. the ideal solution). The reference point approaches, considering discrete variables or not, depends on the definition of an achievement scalarizing function by reference point (aspiration levels) for the objective functions (Demirtas & Üstün, 2008; Wierzbicki, 1980). These approaches, by minimizing the distance from the reference point, attempt to provide non-dominated set.

Among the interactive weighted Tchebycheff procedure (IWTP) or other achievement scalarizing functions for a multi-objective mixed-integer linear programming problem (MOMILP) (Alves & Climaco, 2004; Steuer, 1986; Steuer & Choo, 1983; Karaivanova *et al.*, 1993; Karaivanova *et al.*, 1995; Vassilev & Narula, 1993; Narula & Vassilev, 1994), Steuer and Choo (1983) use lexicographic weighted Tchebycheff program that have the advantage of presenting every efficient solution of the non-concave MOP and being non-dominated. Reeves and Macleod (1999) presented RLTP as an alternative to decrease the set of non-dominated solutions in a Tchebycheff framework. The RLTP method uses the systematic mechanism for reducing non-dominated solution till it achieves the most preferred solutions for the DM. This method applies reservation levels (RLs) based upon the DM's opinion to reduce the objective space. Reeves and Macleod (1999) conducted several experiments to compare the performance of the RLTP and IWTP, and those experiments showed that the RLTP is more flexible than the original IWTP and produce solutions of similar quality. Hence, this paper suggests the RLTP method for three main reasons as follows:

- The need for an interactive MOP method (necessity of using the DM's preferences; reservation levels),
- Its efficiency considering the non-convex nature of the HRL problem, and
- Its optimality in comparison with the other IWTP methods.

The RLTP method is elaborated as follows:

4.2. Reservation Level Tchebycheff Procedure (RLTP) method

The IWTP (Steuer & Choo, 1983) is a weight space reduction method. The RLTP method is an alternative approach to reduce a set of non-dominated solutions. The RLTP method is shown to be more flexible than the original IWTP, while producing solutions of similar high quality. The RLTP method can be described in terms of four steps as follows (Reeves & Macleod, 1999):

1. Initialization

1.1. Determine the number of solutions, N to be presented to the DM at each iteration, where $N \geq P$, and P is the number of objective functions.

1.2. Compute a reference objective vector (y^u), by solving P single objective problems for use in solving the Tchebycheff program in Step 3.

$$y^u = \left(y_1^u, y_2^u, \ldots, y_P^u\right):\ y_k^u = \min\{f_k(x)\,;\, x \in X\} - \varepsilon_k \qquad \forall k = 1 \text{ to } P$$

where ε_k are small positive scalars used in the solution procedure of Tchebycheff programs.

1.3. Set $\mathrm{RL}_k = +\infty$ for $k=1,\ldots,P$.

1.4. Specify the maximum number of iterations.

2. Sampling

With the use of formulation (30), generate a group of $2N$ dispersed weight vectors (Steuer, 1986; Steuer & Choo, 1983).

$$\Lambda = \left\{ \lambda \in R^P \,\middle|\, \lambda_k \in (0,1), \sum_{k=1}^{P} \lambda_k = 1 \right\} \tag{30}$$

3. Solution

In this step, solve the associated Tchebycheff program (31-34) for each weighted vector λ that is generated in Step 2.

$$\min\left\{ \alpha - \rho \sum_{k=1}^{P} f_k(x) \right\} \tag{31}$$

subject to

$$x \in X \tag{32}$$

$$\alpha \geq \lambda_k \left(f_k(x) - y_k^u \right) \qquad \forall k = 1, \ldots, P \tag{33}$$

$$f_k(x) \leq \mathrm{RL}_k \qquad \forall k = 1, \ldots, P \tag{34}$$

According to Steuer and Choo (1983), ρ is a small positive scalar suggested to be between 0.0001 and 0.01.

Present the *N* maximally dispersed solutions to the DM using the method presented in (Steuer, 1986; Steuer & Choo, 1983). If the DM decides to continue to search for a better solution, proceed to Step 4. Otherwise, the DM selects the most his/her preferred solution and stop.

4. Adjustment

In this step and Step 3 of final iteration, the DM participates more actively on interactive way to adjust RLs. According to the DM's considerations, the current solutions should be divided to more and less preferred subset, adjust RLs and return to Step 2.

There are two points for adjusting RLs: (1) RLs for each *k* must be set worse than or equal to the worst value for that objective among the current more preferred solutions, (2) at least one RL must be set better than an objective value of a current less preferred solution. If the DM accepts, the RLs can be adjusted automatically by RLTP rather than by the DM (see Eq. (35)):

$$RL_k = MPWV_k - r\,(MPWV_k - CSWV_k) \tag{35}$$

where:
$CSWV_k$ The worst value over the set of all current solutions,
$MPWV_k$ The worst value over the subset of the most preferred current solutions,
r Reduction factor between 0 and 1(smaller values for r correspond to faster rates of objective space reduction).

5. Case study

This paper demonstrates our approach by a case study originally developed by Mete and Zabinsky (2010). The case is based on discussions with an emergency management coordinator of a large Seattle medical center about possible Seattle earthquake and the needs for medical supplies. Historical disaster data and statistical analyses on two causes of disasters in Seattle [http://seattlescenario.eeri.org/documents/EQScenarioFullBook.pdf, accessed 30 May 2013 and http://www.crew.org/sites/default/files/CREWCascadiaFinal.pdf, accessed 18 July 2013] are used to generate scenarios and face the problem in much more realistic way.

There are two faults, Seattle fault and Cascadia fault, which are expected to cause an earthquake in Seattle city. Their magnitudes are expected to be 6.7 and 9.0, respectively [http://seattlescenario.eeri.org/documents/EQScenarioFullBook.pdf, accessed 30 May 2013 and http://www.crew.org/sites/default/files/CREWCascadiaFinal.pdf, accessed 18 July 2013]. According to their impact, people will need medical supplies in the nearest hospitals to them in the aftermath of the earthquake.

The demand of hospitals depends on the occurrence location of the disaster and the time of day. For instance; Cascadia is a residential area and many people are there at non-working hours of the day. If the disaster strikes during non-working hours, the demand of hospitals in Cascadia is expected to be extremely high. On the other hand, if the disaster strikes in the Seattle area during working hours, a huge demand is expected in the nearby hospitals. Hence, the case study considers six scenarios according to time (working (denoted W), rush (denoted R) and non-working (denoted N) hours) and location of the disaster (Seattle fault and Cascadia fault). The case study assumes 168 hours in a week include 48 working hours (Monday to Saturday; 6 days × 8 working hours), 30 rush hours (6 days × 5 rush hours) and 90 non-working hours (6 days × 11 non-working hours + Sunday; 24 hours). According to the occurrence probabilities of Seattle fault and Cascadia fault (0.4 and 0.6), the probabilities of the six scenarios are presented in Table 2.

Table 2
Probabilities of scenarios

Scenario	Seattle fault			Cascadia fault		
	W	R	N	W	R	N
Probability	0.11	0.07	0.22	0.17	0.11	0.32

In this case study, ten hospitals (demand points) are certain and marked in yellow in Figure 1. The demand of each demand point is estimated based on both population density and predicted damage in each scenario. Population density; in Seattle city, people are in downtown (vulnerable to Seattle fault) in working hours and they are in residential areas, the northern part of Seattle (is vulnerable to Cascadia fault), in non-working hours. The demand is then expected to be high for hospitals near residential areas in non-working hours for the Cascadia fault. On the other hand, it is predictable that hospitals near downtown will need huge medical supplies in working hours. The case assumes that the demand is balanced in whole parts of the city in rush hours. Table 3 provides estimated demand of hospitals in each scenario. Five candidate warehouses are considered in the case and marked in Figure 1. Warehouse opening cost (including personnel, equipment and maintenance cost) and capacity, and the cost/capacity ratio (additional measure is defined for analyzing the results in next section) are showed in Table 4.

Fig. 1. Seattle map: hospitals and possible warehouses

Table 3
Hospitals demand (d_{jk})

Hospital	Seattle fault			Cascadia fault		
	W	R	N	W	R	N
1	6313	6042	9491	9234	8306	13,624
2	3409	3857	3994	5296	3958	7149
3	4969	3732	6466	5922	5147	9357
4	1532	3454	4254	5422	7114	7507
5	2293	3487	4836	7185	8750	10,258
6	3129	2508	2913	3801	1814	2112
7	10,021	5932	3869	12,410	6830	7639
8	7342	4617	4213	9134	3803	5924
9	5723	3686	1773	6784	4036	4382
10	5214	3498	2189	6048	3006	3861

Table 4
Warehouse capacities and fixed cost (F_i, γ_{ik})

Warehouse	Capacity (10^3 units)	Cost ($\$10^6$)	Cost/capacity ($\$10^4$/unit)
1	20	25	0.125
2	25	20	0.080
3	30	12	0.040
4	10	6	0.060
5	5	12	0.240

Since it is possible that the amount of usable medical supplies in the warehouses changes following an event occurrence because of probable damages to the warehouses, the case study considers the proportion of unusable supply k in warehouse i in scenario s, noted ρ_{iks}. This parameter is estimated based on possible damage to the warehouses building aftermath an earthquake is occurred in the Seattle fault or Cascadia fault and is provided based on different scenarios in Table 5.

Table 5
Proportion of unusable supplies in scenarios (ρ_{iks})

Warehouse	Seattle fault			Cascadia fault		
	W	R	N	W	R	N
1	0.082	0.069	0.091	0.080	0.0107	0.083
2	0.096	0.070	0.078	0.093	0.073	0.070
3	0.099	0.086	0.086	0.074	0.086	0.085
4	0.087	0.091	0.086	0.072	0.080	0.074
5	0.062	0.057	0.073	0.085	0.093	0.090

On the similar way, the case study estimates the transportation times between warehouses and hospitals according to the possible damage to the routes and their usable traffic capacity following an event based on:
[http://seattlescenario.eeri.org/documents/EQScenarioFullBook.pdf, accessed 30 May 2013 and http://www.crew.org/sites/default/files/CREWCascadiaFinal.pdf, accessed 18 July 2013]. These transportation times are provided in Table 6.

To ship the medical supplies through predetermined routes, vehicles are needed after disaster. Hence, the case study assumes there are unlimited available identical vehicles (trucks) with a capacity of 7000 units for pre-disaster planning. The bi-objective mixed integer model determines the suitable number of vehicles that are needed to preposition in each warehouse.

To determine the upper bound of tolerable difference of fairness level between two demand points (Δ_{pq}), we consider the opinions of humanitarian logistic practitioners and set it to half of the average of weighted unsatisfied demand of the hospitals.

For simplicity reasons and clarity of presentation, this paper considers only a single type of medical supplies, although if there are at least 10 medical items needed in the aftermath an earthquake (according to the interviews with the emergency management coordinator of a large Seattle medical center).

Table 6
Transportation times for scenarios (t_{ijks})

Warehouse	Hospital	Seattle fault			Cascadia fault		
		W	R	N	W	R	N
1	1	77	210	44	44	90	11
	2	105	210	60	60	90	15
	3	27	27	18	18	18	9
	4	15	15	10	10	10	5
	5	105	210	60	60	90	15
	6	112	210	64	64	90	16
	7	147	245	84	84	105	21
	8	18	18	12	12	12	6
	9	24	24	16	16	16	8
	10	18	18	12	12	12	6
2	1	20	40	10	30	60	20
	2	14	14	7	21	21	14
	3	133	133	76	57	76	19
	4	126	245	72	72	105	18
	5	26	26	13	39	39	26
	6	32	50	16	48	75	32
	7	42	60	21	63	90	42
	8	133	245	76	76	105	19
	9	140	245	80	80	105	20
	10	119	245	68	68	105	17
3	1	98	245	56	56	105	14
	2	112	175	64	64	75	16
	3	112	245	64	64	105	16
	4	98	245	56	56	105	14
	5	14	14	7	21	21	14
	6	8	8	4	12	12	8
	7	24	24	12	36	36	24
	8	45	105	30	30	70	15
	9	51	105	34	34	70	17
	10	15	15	10	10	10	5
4	1	24	24	12	36	36	24
	2	34	50	17	51	75	34
	3	119	119	68	51	68	17
	4	119	119	68	51	68	17
	5	34	34	17	51	51	34
	6	30	50	15	45	75	30
	7	40	70	20	60	105	40
	8	54	90	36	36	60	18
	9	57	105	38	38	70	19
	10	51	51	34	34	34	17
5	1	147	210	84	84	90	21
	2	56	56	28	84	84	56
	3	154	154	88	66	88	22
	4	66	66	44	44	44	22
	5	81	108	27	189	189	108
	6	72	96	24	168	168	96
	7	36	48	12	84	84	48
	8	69	69	46	46	46	23
	9	75	75	50	50	50	25
	10	63	90	42	42	56	21

6. Computational results

In order to show the applicability and usefulness of the presented model and the solution methods, RLTP and ε-constraint are coded in general algebraic modeling system (GAMS) and integrated to the bi-objective mixed integer model to solve the case study data. GAMS/CPLEX solver is capable of solving mixed-integer programming (MIP) models. A PC with 1.73 GHz seven processors and WINDOWS operating system is used as a technical platform.

6.1. RLTP method

An additive utility function based on normalized values of the objectives is applied to simulate the DM preferences with the weight of 0.5 considered for both objectives. Although the DM can determine RLs for any objective in the RLTP, this paper uses Equation (35) to automatically tighten RLs at each iteration with predetermined constant rates (r = 0.3) if the DM does not tighten RLs. In order to clarify the way the algorithm solves the problem, this paper presents step-by-step the solution approach for the case study with use of the RLTP method and its four-step algorithm as follows according to Fig. 2:

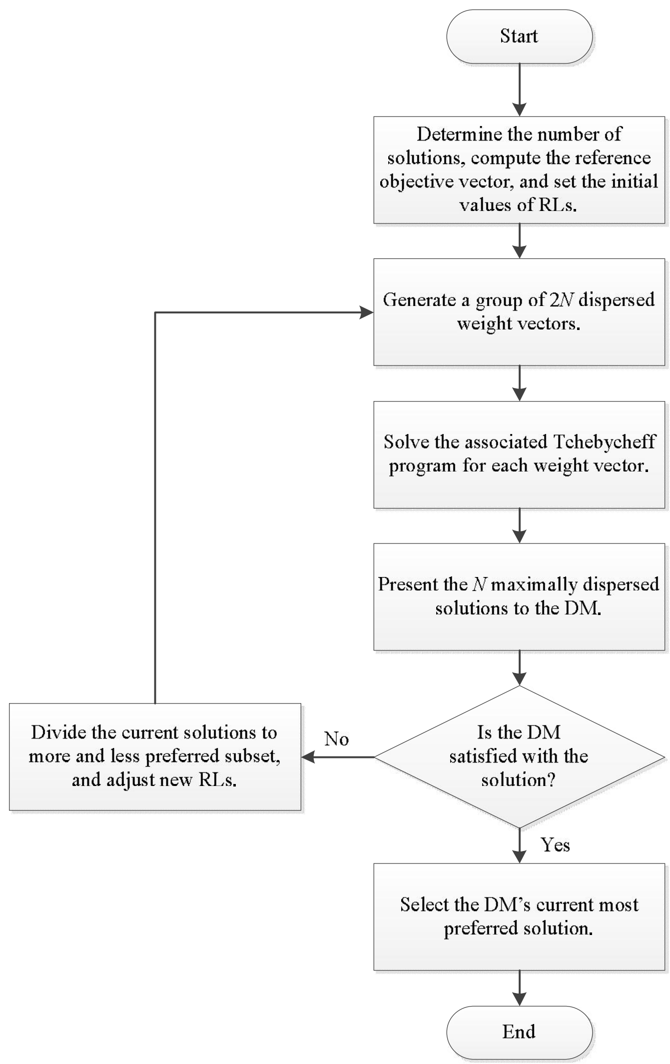


Fig. 2. Flowchart of the RLTP procedure

Step 1. Initialization

In the first step, three solutions (N=3) are presented to the DM in each iteration where P=2. To determine the unknown ideal solution (z^*), the single objective problems are solved (z^*= min $\{f_k(x_k)| x \in S\}$). Then, the reference objective vector (y^u) is computed by y^u= min $\{f_k(x_k) \mid x \in S\}$ $-\varepsilon_k$, where ε_1= 1 and ε_2= 10E+11. Table 7 shows the ideal solution and the reference objective vector.

Table 7
Ideal solution and reference objective vector

The optimal solution for single objective model	Z_1		Z_2 (10^{14})
Optimal solution forZ_1 =	(81.988	,	1.01633)
Optimal solution forZ_2 =	(226.947	,	0.328666)
Z^*: ideal solution =	(81.988	,	0.328666)
y^u: reference objective vector =	(80.988	,	0.327666)

Set $RL_k = +\infty$ for k = 1,2 where RL_k is used as the reservation level for the k-th objective.

Step 2. Sampling

In the second step, six dispersed weight vectors (2N = 6) are generated randomly with regards to Steuer (1986). Table 8 shows the generated dispersed weight vectors group.

Table 8
Dispersed weight vectors

k	1	2	3	4	5	6
λ_1	0.2	0.5	0.69	0.83	0.3	0.90
λ_2	0.8	0.5	0.31	0.17	0.7	0.10

Step 3. Solution

In the third step, the associated Tchebycheff program for each weight vector λ_i is solved with considering ρ = 0.01. The associated results are shown in Table 9. Fig. 3 shows increasing weight for the average response time (Obj1) causes the total cost (Obj2) to increase. Also, decreasing weight for Obj1 causes Obj2 to decrease. Therefore, it seems that by raising the goal for each of the objectives, we create more space for other objectives to be improved. It is also concluded that there are some positive correlations between the total cost and the average response time.

Table 9
Associated results of Tchebycheff program for each weight vector

k	1	2	3	4	5	6
Z_1	127.795044	104.311686	99.238121	92.859925	113.87898	87.78636
Z_2 (10^{13})	1.01709	1.81370	2.98402	4.18384	1.18428	4.41987

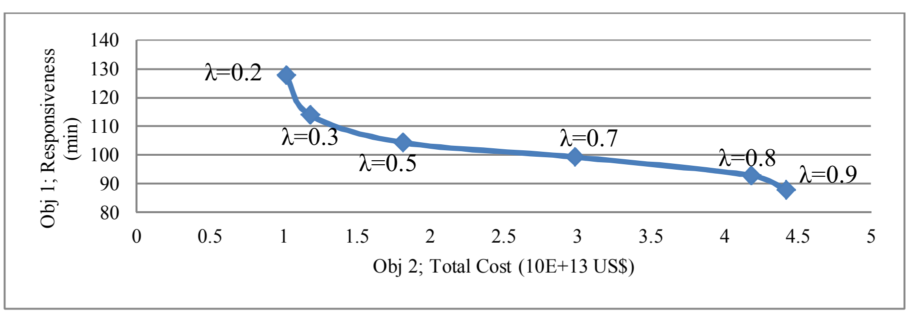


Fig. 3. Results of sensitivity analysis for IWTP coefficient

The maximally dispersed solutions obtained by applying the filtering method, are presented to the DM. For more information about filtering method, the reader can refer to (Steuer, 1986; Steuer & Choo, 1983). If the DM is satisfied with these results, he/she must select his/her current most preferred solution and the algorithm stops. Otherwise, if the DM wishes to continue to search for an improved solution, go to Step 4.

Step 4. Adjustment

According to the DM's considerations, the current solutions are divided to more and less preferred subset (see Table 10).

Table 10
The subset of the most preferred current solutions

k	1	2	5
Z_1	127.795044	104.311686	113.87898
Z_2 (10^{13})	1.01709	1.81370	1.18428
$U(z)$	0.193	0.1525	0.1535

The DM selects solution #2 that is showed in Table 10 as the most preferred solution. The new value for RL_2 is computed using Eq. (35), and RL_1 is adjusted by the DM as follows:

RL_1= 1.26925E+02, RL_2= 1.81370E+13-0.3 × (1.81370E+13-4.18384E+13) = 2.52474E+13

After adjusting the new RLs, return to Step 2. After two iterations, the DM selects his most preferred solution (z_1 = 104.166727, z_2 = 1.79403E+13), and the algorithm stops. Table 11 shows the most preferred RLTP solution in the first two iterations. Table 12 shows the RLs in the each iteration.

Table 11
Most preferred RLTP solutions

Iteration	Z_1	Z_2 (10^{13})	U(z)
1	104.311686	1.81370	0.1525
2	104.166727	1.79403	0.1510

Table 12
Reservation levels

iteration	1	2
RL_1	+ ∞	1.26925E+02[a]
RL_2	+ ∞	2.52474E+13

[a] RL_2 is tightened by the DM.

Fig. 4 shows Pareto curve that is concluded by the RLTP method. There is no optimal solution for this problem, and the RLTP method simply presents a more preferred solution to the DM in an interactive procedure. By changing the input parameters, different solutions are achieved by the RLTP that the DM should include in his preference.

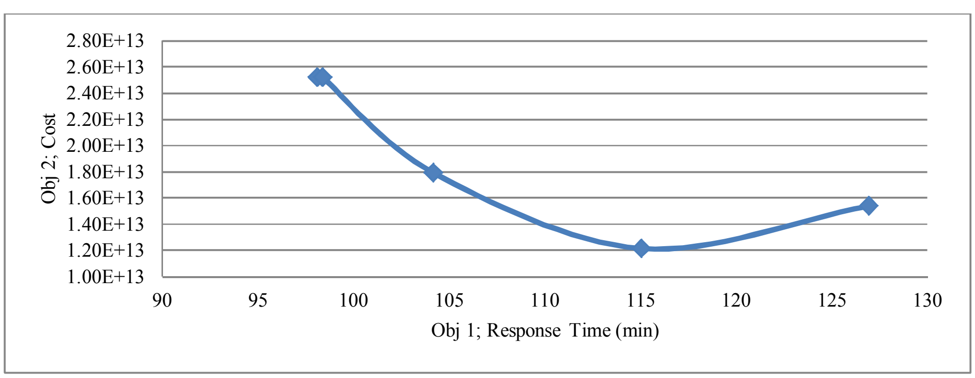


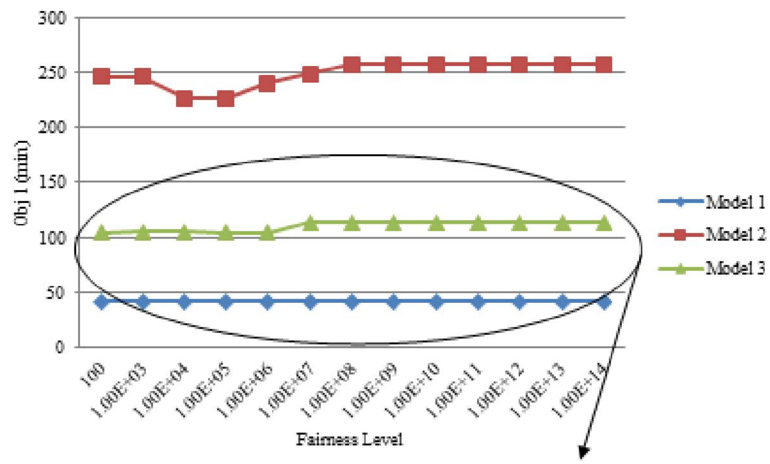
Fig. 4. Pareto curve

5.2. Sensitive analysis

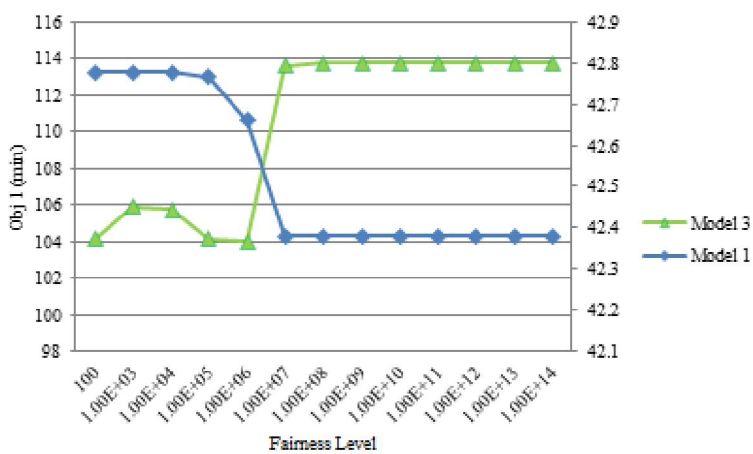
To emphasize the importance of simultaneously considering the total cost and the average response time, as incorporated in our proposed model, the following three models are defined for sensitivity analysis:

1. *Model* 1 consists of the average response time of relief logistic network (Obj1) and its related constraints;
2. *Model* 2 consists of the total cost of relief logistic network (Obj2) and its related constraints;
3. *Model* 3 IWTP model consists of the objective function (Obj3) calculated by Equation (20) and its related constraints.

Fig. 5 shows the performance of the three Models (based on Obj1) versus the changes of the fairness level parameter (δ_{pq}). It is necessary to set a bound for the fairness level constraint because the social disaster may happen in affected areas. Hence, it is recommended to adjust the upper bound of the fairness level in [10^5 - 10^6] based on Figure 5 due to simultaneously tradeoff between objectives value and fairness factor. There is similar situation about the fairness level parameter and Obj2 (see Fig. 6). Hence, according to this figure it is recommended to adjust parameter in [10^5 - 10^6], too.



(a)



(b)

Fig. 5. (a) Average response time versus the fairness level, (b) Clarification of the interaction between Model 1 and 3

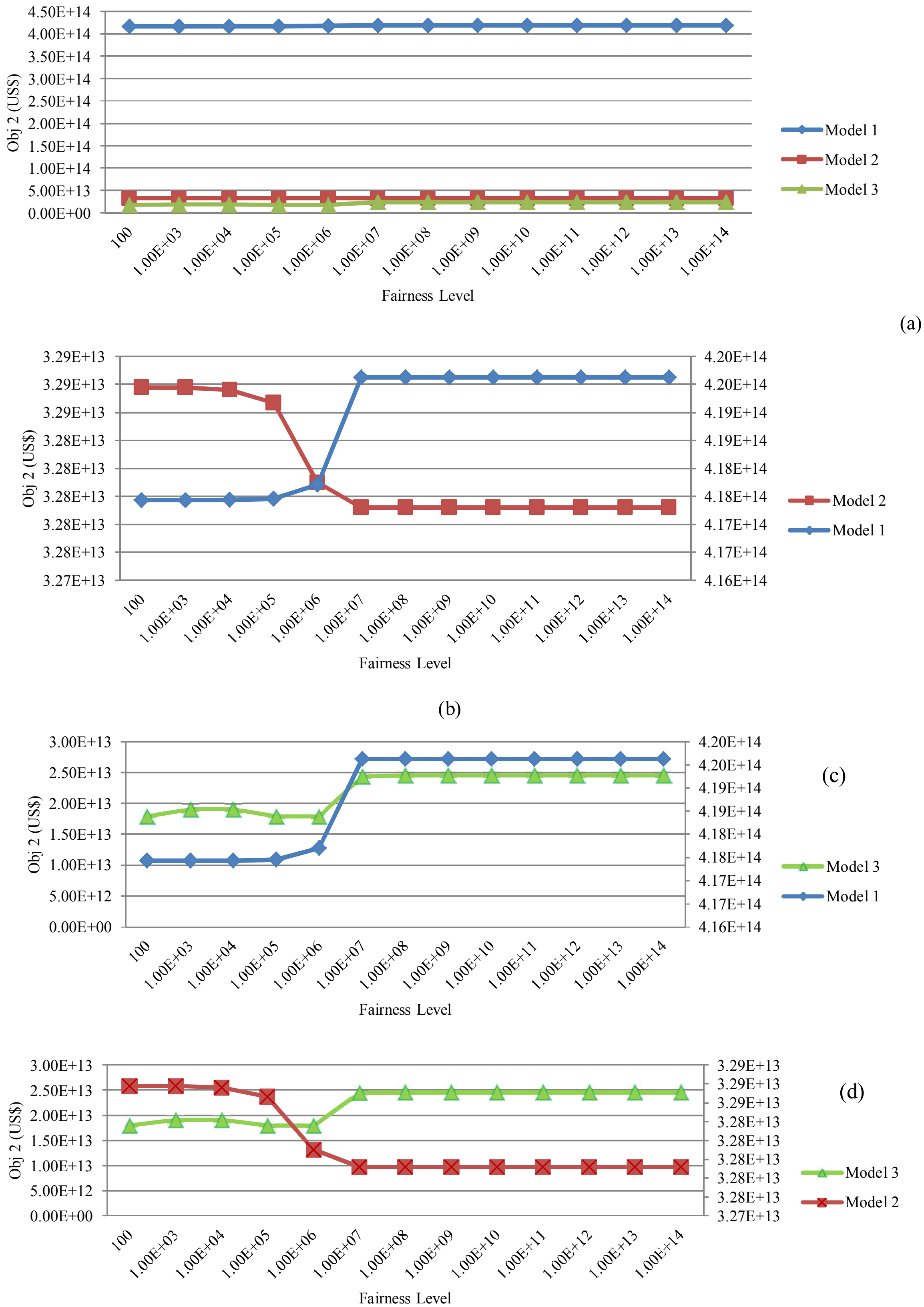
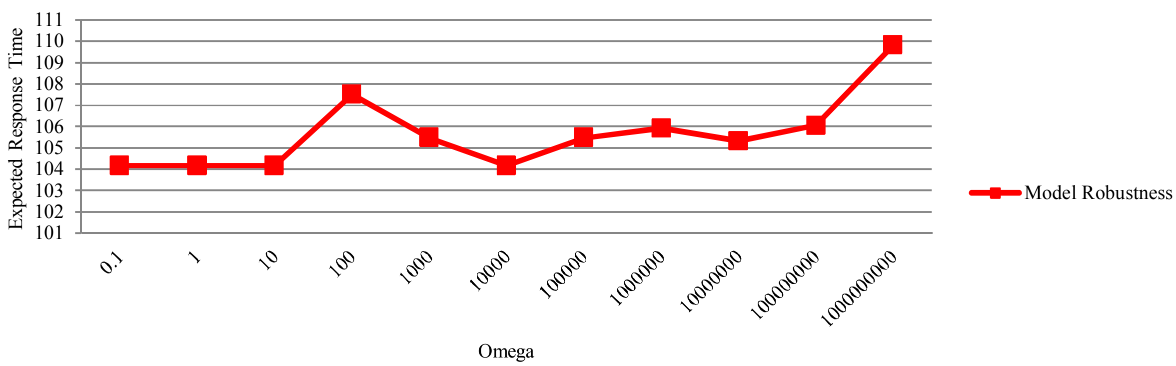
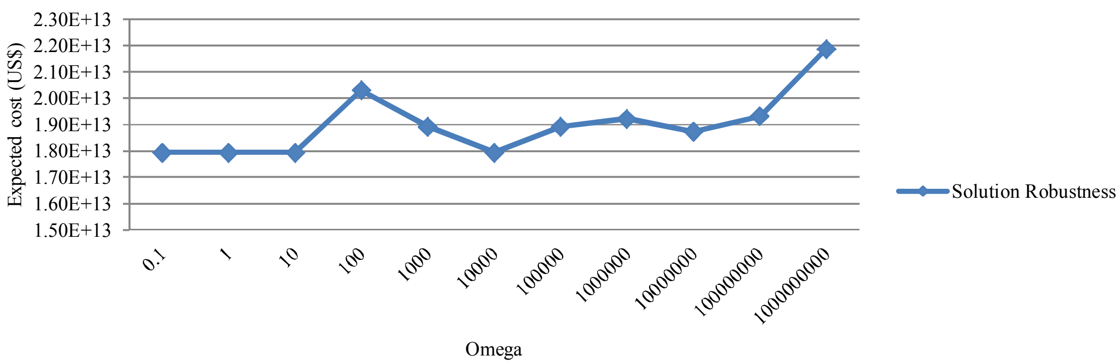


Fig. 6. (a) Total cost versus the fairness level, (b-d) Clarification of the interaction among Model 1, 2 and,

In Fig. 7, a sensitivity analysis is performed for model robustness and solution robustness against the multiplier of model robustness (Omega) in the model. As Figure 7-a demonstrates, the expected average response time will eventually increase with an increase in the value of Omega. On the other hand, the expected cost almost has increasing trend by increasing the value of Omega (see Figure 8-b). It is inferred that increasing in amount of penalty (omega) leads to decreasing the amount of relief items in the relief network, so the expected average response time to deliver relief items to demand point will increase. Hence, the DM should here choose the best value of Omega with considering preventing a huge increase in the expected cost and average response time values (i.e., [0.1 - 10]).



(a)



(b)

Fig. 7. (a) Model robustness and solution robustness, (b) versus Omega

7. Analysis of results

In the previous section, the most preferable solution was presented using the RLTP method. Tables 13-16 show the results of this solution; the warehouses chosen and the amount of relief items pre-positioned at each warehouse are shown in Table 13. The most preferable solution proposes the warehouses 2, 3, and 4 to actively store relief items in preparation for possible earthquake scenarios. Table 14 shows the amounts of relief items that are transported by vehicles on the routes from warehouses to hospitals. The warehouses cannot fully satisfy the demand of the hospitals for all scenarios in our case as shown in Table 15.

There are three important criteria considered in the decision of opening a warehouse: (1) distance to the hospitals, (2) capacity, and (3) operating cost. As the selected warehouses are 2, 3, and 4, an explanation is provided. Indeed, not only warehouses #3 and #4 have the first and second lowest cost/capacity ratio, but also warehouse #3 is the nearest one to the hospital #5 and #6. Warehouse #4 has suitable condition with comparison to warehouse #1 for serving hospital #1, and helping to serve to the middle and downtown hospitals of Seattle in shortage condition, as it is located in the center of Seattle area. Warehouse #1 has the second highest cost/capacity ratio, and also is far from middle hospitals. Therefore, it cannot be selected to help the other warehouses in shortage condition in the center of Seattle. Although, Warehouse #5 can satisfies the demand of the downtown hospitals and can help the other warehouses to serve the hospitals in residential area, it has the highest cost/capacity ratio in comparison with warehouse #4 (that has similar condition), so the model selects warehouse #4. This implies that the model selects the warehouses with low cost/capacity ratio and considers at a second level the distance between warehouses and hospitals, especially in shortage condition when they will be used as support to the other warehouses.

Table 16 shows the number of vehicles that should be assigned to each selected warehouse for each scenario. The total number of vehicles assigned is at most 10, which is required for one of the Cascadia fault earthquake scenario, whereas the other scenarios require fewer vehicles. Four vehicles are used in four out of six scenarios in warehouse 3. Warehouse #4 is in a similar situation and requires two vehicles in four out of six scenarios. Warehouse #2 uses two vehicles in two scenarios, but up to four vehicles in one scenario related to Cascadia fault. Because of the important role of warehouse #2 in serving the hospitals #1 and #2 (see Table 14) and the high probability of scenario 4 to 6 in Cascadia fault, it is recommended to assign the maximum required number of vehicles (four vehicles) to it.

Table 13
The opened warehouses and the corresponding amount of relief items

Warehouse	Amount of prepositioned relief items
2	24423
3	30000
4	10000

Table 14
Transportation network and visited hospitals

Scenario	Warehouse	Hospital									
		1	2	3	4	5	6	7	8	9	10
1	1	-	-	-	-	-	-	-	-	-	-
	2	4781	1877	-	-	-	-	-	-	-	-
	3	-	-	3395	-	739	1566	8489	5810	4191	3682
	4	-	-	-	-	-	-	-	-	-	-
	5	-	-	-	-	-	-	-	-	-	-
2	1	-	-	-	-	-	-	-	-	-	-
	2	-	1363	-	-	-	-	-	-	-	-
	3	-	-	-	-	1014	9	3459	-	-	990
	4	3569	-	1259	981	-	-	-	2112	1178	-
	5	-	-	-	-	-	-	-	-	-	-
3	1	-	-	-	-	-	-	-	-	-	-
	2	9491	3994	-	-	-	-	-	-	-	-
	3	-	-	1872	4212	4836	2884	3869	4206	1756	2168
	4	-	-	4595	-	-	-	-	-	-	-
	5	-	-	-	-	-	-	-	-	-	-
4	1	-	-	-	-	-	-	-	-	-	-
	2	7338	3400	4026	-	-	-	7953	-	-	-
	3	-	-	-	-	5283	1867	2507	7238	1194	4116
	4	-	-	-	3507	-	-	-	-	3694	-
	5	-	-	-	-	-	-	-	-	-	-
5	1	-	-	-	-	-	-	-	-	-	-
	2	3808	2113	3341	-	-	-	-	-	-	-
	3	-	-	-	-	6944	-	5024	1959	2190	1200
	4	2693	-	-	5308	-	-	-	-	-	-
	5	-	-	-	-	-	-	-	-	-	-
6	1	-	-	-	-	-	-	-	-	-	-
	2	8627	4966	-	-	-	-	-	3505	-	-
	3	2750	-	-	5320	8044	-	5451	-	2227	1711
	4	-	-	7152	-	-	-	-	249	-	-
	5	-	-	-	-	-	-	-	-	-	-

Table 15
Unsatisfied demand

Hospital	Scenario					
	1	2	3	4	5	6
1	-	-	-	-	-	137
2	-	21	-	-	40	72
3	43	-	-	-	-	94
4	-	-	43	19	-	76
5	23	-	-	6	-	102
6	32	26	30	39	8	-
7	-	-	-	55	-	77
8	-	32	8	-	39	60
9	-	35	18	-	41	44
10	-	35	22	36	-	39

Table 16
Number of vehicles assigned

Warehouse	Scenario						Maximum	Expected
	1	2	3	4	5	6		
2	1	1	2	4	2	3	4	2.48
3	4	1	4	4	3	4	4	3.68
4	0	2	1	2	2	2	2	1.56
Total	5	4	7	10	7	9		7.72

8. Conclusion

This paper has presented a robust bi-objective mixed-integer programming model for humanitarian relief logistics (HRL) that determines the optimal quantity of emergency supplies and identifies the optimal warehouse locations in a pre-disaster planning phase by considering simultaneously bi-objectives, namely cost and response objectives. An efficient technique has been developed to solve the presented multi-objective model: the Reservation level Tchebycheff procedure (RLTP) method. From the application of this technique on a case study, the experiment results have concluded that the RLTP method has been a proper method to handle the HRL problem. The use of a scenario-based analysis has fostered the robustness of the resolution approach and taken into account the uncertainties linked to the earthquake occurrences. Nevertheless, the model has considered different simple occurrence scenarios rather than a more realistic situation, which could be highly complex as it could represent simultaneous occurrence of events or unexpected chained events.

For future research directions, the mathematical model can be extended in order to integrate the dynamic evolution of the network and the corresponding demand. In fact, in the case of earthquakes, there are different periods of time, on which the information about the demand or situation of routes changes. It would be interesting to consider the knowledge of personnel, who visited the affected areas, for a better planning in different periods of time and integrate this feedback in a dynamic way. Furthermore, optimizing the evacuation of injured people from affected areas is another interesting aspect that can be combined with the general logistic optimization model of relief items distribution.

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