A multi-objective approach in expanding the pre-positioning warehouse networks in humanitarian logistics

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Abstract: In this study, we focus on the structure of the pre-positioning warehouse networks which have a great effect on the response to a disaster. We determine the pre-positioning warehouse network configuration of CARE International with a multi-objective approach using the recent decade data. In addition to the minimisation of the average response time of an item, we also consider the maximum response time and maximum water delivery time as additional objectives. After analysis of the non-dominated solutions, we conclude that CARE International should open a warehouse in Kenya and pre-position 39%–44% of all relief items other than tents to this location while starting to operate the Denmark warehouse instead of the Dubai warehouse.
[Received: 20 March 2018; Revised: 12 September 2019; Accepted: 26 February 2020]

Keywords: pre-positioning; humanitarian relief logistics; warehouse location; network expansion; multi-objective.

Reference to this paper should be made as follows: Yakıcı, E., Karatas, M. and Duran, S. (2021) ‘A multi-objective approach in expanding the pre-positioning warehouse networks in humanitarian logistics’, *European J. Industrial Engineering*, Vol. 15, No. 1, pp.67–102.

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1 Introduction

In the recent decade natural disasters start to be more on the public eye due to the increase in both the number and the impact of the disasters. The 2011 Tohoku Tsunami in Japan and the 2012 Sandy Hurricane in USA cost \$223 and \$52billion to the world economy, respectively. Observing more than 300 disasters per year is the norm nowadays since the millennium whereas that number was around 200 annually before (Guha-Sapir et al., 2016). By the year 2020, the world's population will be very close to eight billion people and unfortunately most of the people will be prone to the effects of the more frequent and more devastating disasters since they are living in states where fragility, conflict and violence (FCV) is observed. According to FCV Group of World Bank (2017), fragility, conflict, and violence is a critical obstacle to decrease poverty and improve the wealth distribution in the states in which two billion people are now living. Unfortunately, World Bank FCV Group predicts that the share of extreme poor living in conflict-affected situations will to rise from 17% of the world population to almost 50% by the year of 2030. With such troublesome demographic and politic environment of the world, disaster relief response gains the utmost importance.

CARE International is a global confederation of humanitarian aid organisations working together to end poverty. In 2016, CARE operated in 94 countries and reached more than 80 million people directly and 256 million people indirectly through the programs it executed. Although CARE's primary aim is to fight poverty, since it is not possible to fight poverty when disasters destroy the hard-won development gains, it also provides life-saving humanitarian assistance to the people affected by disasters in developing countries. CARE reached more than 10 million people in 2015 through its humanitarian response activities and this number is forecasted to be 20 million people by 2020 (CARE, 2014).

In collaboration with a research group from Georgia Institute of Technology, CARE investigate pre-positioning strategy for disaster relief items and completed the establishment of the Dubai, Panama and Cambodia warehouses by 2009 (Duran et al., 2011). When disaster strikes, CARE provides emergency relief items such as food, supplies, water, sanitation and shelter to the affected people from its warehouses to provide fast and effective relief. But as stated above since the number of people to be affected by disasters are expected to be more in the near future and disasters trends are changing due global warming, how to expand such an established pre-positioning network calls for further academic research.

Bozkurt and Duran (2012) work on analysing the pre-positioning network of CARE International with the consideration of changing disaster trends and utilising the historical disaster data between the years of 1977 and 2006 which are grouped into three decades. They show that Panama and Cambodia are robust locations when all three decades are considered but the location of the third warehouse changed from Italy to India in the second decade and settled at Dubai in the last decade ended by the year 2006. This result confirms that the pre-positioning network configuration of CARE International by 2009 takes into account the disaster trends up to the year of 2006. But due to the shift of the third warehouse towards South Africa, authors proceed with studying the most recent disaster data of 2007–2010 these days and suggest that a fourth warehouse should be opened in Kenya.

In this study we improve the work of Bozkurt and Duran (2012) in two ways. We use the most recent decade data (2007–2016) from the Emergency Events Database (EM-DAT, 2017) in our mathematical model and also apply a multi-objective approach to the expansion problem to obtain robust solution. The motivation of this research arises from the requirement of taking the problem from different point of views which may contribute to the results of the mentioned previous study. As in many examples in the literature of location analysis, we have the curiosity about the effect of decreasing maximum response time on the setting which has only decreasing average response time. We also want to see the results when the most vital item 'water' is given a priority in all of the delivered items. Moreover, an additional contribution of our study is updating the results by including the most recent data.

The remainder of this paper is organised as follows: in Section 2, we provide a literature review of the location – allocation problems in the humanitarian logistics applications. Section 3 presents the mathematical formulation developed for the studied problem. We present the problem data, numerical results and discuss the solutions in Section 4. To test the performance of our proposed model under different demand realisations, we also carry out several sensitivity analysis runs at the end of Section 4. Section 5 concludes the paper.

2 Literature review

Nikbakhsh and Farahani (2011) defines humanitarian logistics as the logistic component of the disaster management system managing the procurement, storage and transportation of relief items, mobilisation of the human resources, equipment and machinery and evacuation of the affected people. In this study we focus on the pre-positioning of relief items, strategically locating the relief items in warehouses, to enable fast and efficient disaster relief. In the last decade, pre-positioning idea in humanitarian logistics is investigated via operational research techniques (Campbell and Jones, 2011). In this section we review the literature on warehouse locations for relief items with respect to the operational research techniques utilised in those studies.

As expected, the initial works utilise a deterministic approach such as Hale and Moberg (2005). They formulate the problem of establishing a network of secure site locations as a set cover problem. Later studies incorporate the uncertainties inherit in the disaster relief management, such as the locations and the number of people affected from the disasters, into the mathematical models by considering a set scenario. Instead of using scenarios to incorporate the randomness inherit in the disaster management, Mete and Zabinsky (2010) propose a two-stage stochastic optimisation approach for the problem of optimal storage and distribution of relief supplies. Rawls and Turnquist (2010) also develop an emergency response planning approach to determine the location and quantities of emergency supplies for natural disasters and they employ a two-stage stochastic program. They consider uncertainty in demand and transportation network availability and suggest a heuristic to solve large-scale instances of the problem. The authors extend their model with additional service quality constraints in their following work (Rawls and Turnquist, 2011). Duran et al. (2011) consider an MIP model to address the location – allocation problem of pre-positioning relief items for a global humanitarian organisation. They choose their objective as minimisation of the average travel time of relief items over the scenarios considered which represents disaster location-relief item needs worldwide within two-week time windows.

Another but less often used approach to consider uncertainties in MCLP is the inclusion of chance-constraints into the formulation. Murali et al. (2012) consider the location problem of capacitated facilities using a MCLP formulation with a loss function and chance constraints. Renkli and Duran (2015) suggest an MIP model with chance constraints in order to pre-position warehouses optimally in a potential affected area and determine the amount of items to be stored in those warehouses. Tofighi et al. (2016) address a humanitarian logistics network design problem and also develop a two-stage stochastic programming model. The locations are determined in the first stage, while a relief distribution plan is developed with respect to several criteria in the second stage. A differential evolution algorithm is utilised to solve the problem.

Recently, the location – allocation problem is studied with multi-objective and multi-criteria perspectives. Bastian et al. (2016) uses stochastic, mixed-integer, weighted goal programming to optimise the warehouse network structure. Yılmaz and Kabak (2016) also consider a similar problem to locate the main and local distribution centres simultaneously via a multi-objective decision model. The objectives are selected as the distance between the centres and demand points and the number of centres. They also utilise a goal programming approach but conclude that completion time increases with the problem size. Due to the high computational time requirements, the studies considering the combined network designs for health, temporary accommodation and relief warehouses focus on the advancement of solution techniques as well as the modelling. Üster and Dalal (2017) consider the integrated emergency preparedness network considering evacuation assignments, opened shelters and relief item distribution centre management. They also consider two objectives, namely the travel distance and total cost to incur in the network and adopt a benders decomposition approach to solve large-scale instances. The health centres and relief item distribution integration is addressed by Haghi et al. (2017) again with a multi-objective programming model and solved via robust optimisation approach and developed heuristics.

The choice of the travel time of the relief items as the objective is verified by the recent work of Richardson et al. (2016) which investigates the factors important to humanitarian organisations while choosing the pre-positioning warehouse locations. The speed of emergency response is identified as the top factor using a Delphi study. Therefore, rather than cost consideration which is common in the literature as mentioned above, in this study we solve the location – allocation problem for a specific global humanitarian aid NGO considering three objectives all of which are related with the speed of relief item delivery. Our solution methodology is a classical scalarisation approach which converts the multi-objective problem into a single objective problem. This method combines all objectives into a single weighted additive function. Since the solution obtained from this method is highly dependent on the selected weight vector, we solve the problem using various weights.

In their study, Mejia-Argueta et al. (2018) propose a multi-criteria optimisation methodology for integrated humanitarian logistic operations in emergency disaster scenarios. Their approach basically considers the emergency facility locations, prepositioning of humanitarian aid, and evacuation and distribution allocation during floods with the objectives of minimising the maximum evacuation flow-time, the maximum distribution flow-time, and total cost of operations. Jalali et al. (2018), on the other hand, adopt a passive defence approach which seeks to locate humanitarian aid facilities based on four criteria as population density, user appropriateness, access level and degree of confinement. In a recent study, Rodríguez-Espíndola et al. (2018), approach the problem from a different perspective and develop an integrated multi-objective optimisation and geographical information system. Along with determining the location of emergency facilities, stock prepositioning, resource allocation and relief distribution, their proposed approach also determines the number of actors required to avoid shortages or convergence. Interested reader can also refer to Gutjahr and Nolz (2016)'s review paper which analyses studies that incorporate multi-criteria optimisation techniques to the management problems related to natural disasters, epidemics or different forms of humanitarian crises. Additionally, Jabbour et al. (2019) and Banomyong et al. (2019) provide a more systematic survey on the humanitarian logistics and supply chain management issues and specify a number of research gaps in the domain.

Considering the humanitarian crises in East Africa, Dufour et al. (2018) analyse the benefits of adding a new distribution centre in Kampala, Uganda, to the existing network of the United Nations Humanitarian Response Depot (UNHRD). Using real data, the authors employ an integrated solution methodology which includes fieldwork, simulation, optimisation and statistical analyses to evaluate the cost effectiveness of prepositioning a distribution centre in Kampala. In particular they first perform a field study in Italy, the UAE and Uganda to collect real-world data. In the next step, for the prepositioning problem, they develop a network flow formulation. Next, they solve the optimisation problem for 5,000 different simulations of demand scenarios across East African delivery points. Finally, they assess the results for both cases with and without the inclusion of the proposed regional distribution centre.

3 Mathematical model definition

We approach the pre-positioning warehouse network of CARE International with a model which includes warehouse location and item assignment decisions. The mathematical modelling of such a network requires the following index sets, parameters, and variables.

Sets and indices

$i \in I$ set of candidate locations for warehouses

$d \in D$ set of disaster types

$j \in J$ set of demand points

$r \in R$ set of relief items

$e \in E$ set of demand instances

$g \in G$ set of objectives.

Parameters

N maximum number of warehouses allowed to be activated

Q total relief item inventory

P_e probability of occurrence for demand instance e (considered equal for each demand instance)

t_{ij} response time from warehouse i to demand point j

t'_{jr} response time from suppliers to demand point j for item r

d_{dje} number of affected people at demand point j by disaster of type d for demand instance e

p_{djr} probability of item r being required at demand point j by a person affected by a disaster of type d

a_{djr} quantity of item r required by a person affected by a disaster of type d in demand point j

d'_{jer} expected demand for item r at demand point j in demand instance e

w_g weight of objective g.

Decision variables

y_i 1 if warehouse i is activated, 0 otherwise

q_{ir} quantity of item r held at warehouse i

x_{ijer} quantity of item r supplied to demand point j from warehouse i for demand instance e

x'_{jer} quantity of item r supplied to demand point j from suppliers for demand instance e.

According to the notation given above, we formulate the model as a mixed integer programming model given as follows:

Objective function

$$z = \min \sum_{g \in G} w_g z_g \tag{1}$$

The objective function (1) aims to minimise the weighted sum of all three objectives z_1, z_2 and z_3.

Constraints

$$z_1 = \sum_{e \in E} P_e \left(\frac{\sum_{j \in J} \sum_{r \in R} x'_{jer} t'_{jr} + \sum_{i \in I} \sum_{j \in J} \sum_{r \in R} x_{ijer} t_{ij}}{\sum_{j \in J} \sum_{r \in R} d'_{jer}} \right) \tag{2}$$

$$z_2 \geq \frac{\sum_{j \in J} \sum_{r \in R} x'_{jer} t'_{jr} + \sum_{i \in I} \sum_{j \in J} \sum_{r \in R} x_{ijer} t_{ij}}{\sum_{j \in J} \sum_{r \in R} d'_{jer}}, \quad \forall e \in E \tag{3}$$

$$z_3 \geq \frac{\sum_{j \in J} x'_{je7} t'_{j7} + \sum_{i \in I} \sum_{j \in J} x_{ije7} t_{ij}}{\sum_{j \in J} d'_{je7}}, \quad \forall e \in E \tag{4}$$

$$d'_{jer} = \sum_{d \in D} a_{djr} p_{djr} d_{dje} \qquad j \in J, e \in E, r \in R \tag{5}$$

$$\sum_{i \in I} x_{ijer} + x'_{jer} \geq d'_{jer} \qquad j \in J, e \in E, r \in R \tag{6}$$

$$\sum_{j \in J} x_{ijer} \leq q_{ir} \qquad i \in I, e \in E, r \in R \tag{7}$$

$$q_{ir} \leq Q y_i \qquad i \in I, r \in R \tag{8}$$

$$\sum_{i \in I} \sum_{r \in R} q_{ir} \leq Q \tag{9}$$

$$\sum_{i \in I} y_i \leq N \tag{10}$$

$$x_{ijer}, x'_{jer}, q_{ir} \geq 0 \qquad i \in I, j \in J, e \in E, r \in R \tag{11}$$

$$y_i \in \{0, 1\} \qquad i \in I \tag{12}$$

The travel time of a relief item from the pre-positioning warehouse to the affected people is assumed to be equal to the summation of the flight time of a cargo aircraft from the pre-positioning warehouse where the relief item is present to the demand point where the affected people is with an additional preparation period of one day. We also assume that if the pre-positioning warehouse inventory is not sufficient to meet the demand, then the global suppliers provide the relief items with a response time of two-weeks (as in Duran et al., 2011) to the affected people independent of their location. Hence, the *average response time* of a relief item represented by constraint (2) is calculated as the weighted sum of these two response times, response times from the pre-positioning warehouse and from the global suppliers, where weights are equal to the proportions of demand satisfied by each resource. Mathematically, $\frac{x'_{jer}}{\sum_{j\in J}\sum_{r\in R} d'_{jer}}$ and $\frac{x_{ijer}}{\sum_{j\in J}\sum_{r\in R} d'_{jer}}$ serve as weights of t'_{jr} and t_{ij}, respectively. And, the first expression is equal to the proportion of the satisfied demand of item r by global supplier for demand point j in the total satisfied demand of all items for all demand points, while the second one is equal to the proportion of the satisfied demand of item r by warehouse i for the demand point j in the total satisfied demand of all items for all demand points. Note that *response time* represents the average of all delivery times of all items in a demand instance $e \in E$. We have specified the probability of occurence of instance e as P_e and for this study, they are taken equal for all instances as noted in the explanation of this parameter. Working in conjunction with the objective function (1), the functions on the right-hand sides (RHS) of constraints (3) and (4) compute the values of second and third objectives of our model, respectively. In particular, the first one [RHS of constraint (3)] represents the *maximum response time* to a demand point among all of the instances and the second one [RHS of constraint (4)] represents the *maximum water delivery* time within all instances, where *water delivery time* is the average of all delivery times of water over all demand points, respectively. Constraint set (5) assigns the value of expected demand of each relief item at each demand location for each disaster instance. Constraint set (6) ensures the satisfaction of demand for each relief item at each demand point for each disaster instance. Constraint set (7) ensures that total amount of an item $r \in R$ shipped from a warehouse $i \in I$ cannot exceed the inventory of item r in warehouse i. Constraint (8) set reflects the requirement that if a warehouse is used, it must be activated. Constraint (9) indicates that the total inventory cannot be exceeded. Constraint (10) satisfies that allowed number of open warehouses should not be exceeded. Finally, variable domains are declared in constraint sets (11) and (12).

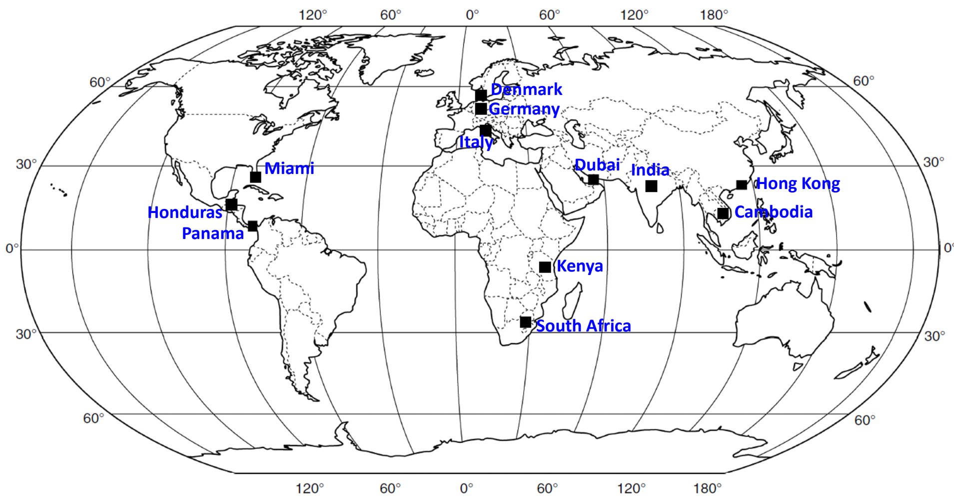
4 Application of the model and results

4.1 Problem data

Similar to Duran et al. (2011) and Bozkurt and Duran (2012), we consider 12 candidate warehouse locations and 22 demand points worldwide (see Figure 1). Seven types of relief items are managed at the pre-positioning warehouses: cold tent, hot tent, household utensils, medical relief items, hygiene sets, sanitation sets and water as assumed by

Bozkurt and Duran (2012). Since all details about the parameter sets are given in the thesis of Bozkurt (2011) and the study of Bozkurt and Duran (2012), for the sake of conciseness, if any parameter is kept same, we do not mention the details about it here in this study.

Figure 1 Candidate locations for warehouses (see online version for colours)



Source: Figure from Duran et al. (2011)

As explained in the previous works (Duran et al., 2011; Bozkurt and Duran, 2012) demand instances are created by grouping disasters occurred in two-week time periods in a region. With this assumption, 237 demand instances are obtained using the disaster data of the decade of 2007–2016. Although the model allows that an affected person in a region may require different combination of relief items according to the region of the world where she/he lives, since there is no evidence for discriminating the regions or disasters with respect to required relief items, we assume all of the affected people will demand the same combination of relief items when a disaster occurs. We assume that all of the affected people in a certain region will need the same demand package and all disaster events in the dataset which is given for the years between 2007 and 2016 will occur in the future, at least for a reasonable strategic planning period, with the same frequency. Total inventory stored in the warehouses is assumed to be the average demand of 237 demand instances which is equal to 38,000,000 units.

4.2 Numerical results

To obtain a robust solution, we solved the developed mathematical model for varying values of objective function weights, w_g. In particular, we generate a possible set of 66 combinations of w_1, w_2 and w_3 such that any weight can take a value from the ordered set {0, 0.1, 0.2, …, 1} and the weights sum up to 1. We also added the special case where all of the weights are equal to each other ($w_1 = w_2 = w_3 = 1/3$). To evaluate the effect of opening additional warehouses, we solved all 67 instances for each value of $N = \{1, 2, …, 6\}$, and obtained a total of 402 solutions. Next, among the 402 solutions, we eliminated the dominated solutions for each N. Finally, we ended up with 83 non-dominated candidate solutions. In particular, we have 31, 25, 10, 5, 6, and 6 solutions for $N = 1, 2, \ldots, 6$, respectively.

We solve each problem instance to optimality using a commercial solver, CPLEX 12.6.2.0 on a PC with Intel(R) Core(TM) CPU@2.7 Ghz, 12 GB memory, and Microsoft Windows 10 64-bit operating system. We observe that the solver has provided optimal solutions within one to six minutes depending on the number of warehouses allowed to be activated and the weights used in the objective function (1). Summary of the results is presented in Table 1. The table reports the objective function term weights and their respective values for the 27 non-dominated solutions for $N = \{3, 4, 5, 6\}$.

Table 1 Objective function values and weights for the non-dominated solutions

#	N	*Weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
1	*3*	0.70	0.10	0.20	66,774.37	333.26	391.38
2	*3*	0.60	0.20	0.20	72,069.30	333.00	388.86
3	*3*	0.30	0.50	0.20	67,052.01	332.64	388.98
4	*3*	0.10	0.70	0.20	75,262.80	332.69	387.45
5	*3*	0.70	0.00	0.30	71,575.57	333.00	387.23
6	*3*	0.00	0.60	0.40	78,826.05	332.60	399.55
7	*3*	0.30	0.00	0.70	72,826.93	332.69	386.75
8	*3*	0.10	0.20	0.70	24,538.02	332.61	392.83
9	*3*	0.00	0.20	0.80	78,823.04	332.59	399.70
10	*3*	0.33	0.33	0.33	75,250.43	332.71	386.54
11	*4*	0.10	0.80	0.10	19,913.53	332.54	398.26
12	*4*	0.30	0.50	0.20	65,450.39	332.58	388.43
13	*4*	0.10	0.40	0.50	22,527.11	332.56	394.18
14	*4*	0.20	0.20	0.60	73,436.13	332.62	386.67
15	*4*	0.10	0.00	0.90	28,043.67	332.67	392.06
16	*5*	0.40	0.20	0.40	68,506.96	333.35	392.93
17	*5*	0.10	0.50	0.40	71,622.75	332.86	389.08
18	*5*	0.30	0.20	0.50	74,548.53	332.94	386.70
19	*5*	0.20	0.20	0.60	72,106.08	332.69	387.34
20	*5*	0.10	0.30	0.60	22,898.97	332.55	393.65
21	*5*	0.20	0.00	0.80	71,054.71	366.08	388.90
22	*6*	0.10	0.40	0.50	22,249.57	332.54	394.17
23	*6*	0.40	0.00	0.60	72,081.54	333.03	388.72
24	*6*	0.20	0.20	0.60	69,481.84	333.35	391.17
25	*6*	0.10	0.20	0.70	24,045.88	332.54	392.74
26	*6*	0.10	0.10	0.80	25,428.05	332.60	392.04
27	*6*	0.10	0.00	0.90	26,210.54	332.59	391.51

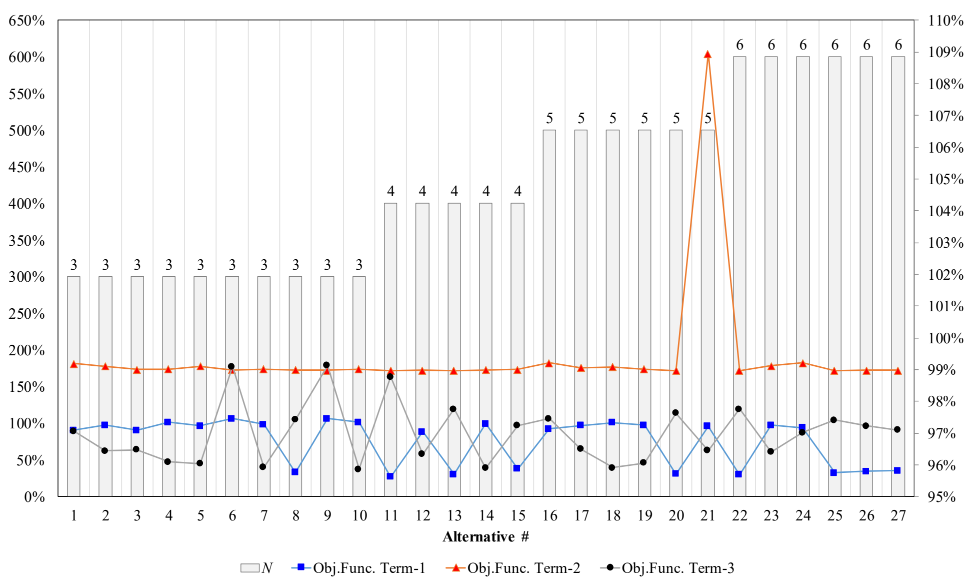
To analyse the performance of non-dominated solutions in Table 1 with respect to the different objective function values, we utilise the solutions with the single objective of z_1 as benchmarks. These solutions also correspond to the solutions in Bozkurt and Duran (2012). Table 2 shows the results for those cases where w_1 is equal to one.

Table 2 Single objective (benchmark) solutions

N	*Weights*			*Obj. func. term values*		
	w_1	w_2	w_3	z_1	z_2	z_3
3	1	0	0	73,968.90	336.00	403.20
4	1	0	0	73,940.72	336.00	403.20
5	1	0	0	73,922.40	336.00	403.20
6	1	0	0	73,925.70	336.00	403.20

Figure 2 shows the deviations of each objective function value of a non-dominated solution from that of its respective benchmark solution (when w_1 is one) in percentage. We compute the deviation of an objective simply by dividing its value with its corresponding benchmark value in Table 2. It should be noted that, first term of the objective function uses the left vertical axis, and others use the right vertical axis.

Figure 2 Deviations of each objective value of a non-dominated solution from the benchmark (see online version for colours)



Tables 3 and 4 show the optimal warehouse locations for each benchmark and non-dominated solution, respectively. It is observed from Table 3 that Denmark, Hong Kong and Kenya are activated warehouse locations in all of the three benchmark solutions. Thus, Denmark, Hong Kong and Kenya locations can be considered as the most robust locations in the network and the expansion should be considered with additional locations to these locations when only the average response time is considered as the objective. To be able to make a similar comment when all three objectives are considered, we need to look at the frequency of the locations in Table 4. The frequency numbers indicate the total number of times when a certain warehouse location is observed in a non-dominated solution. These numbers show that Cambodia, Kenya and Italy are the most preferred locations among all of the candidates with occurrence numbers of 24, 22 and 13, respectively. For a three-warehouse network; Kenya is the only common warehouse location for the case of one objective or three. The benchmark solution suggests opening Denmark, Hong Kong and Kenya warehouses whereas Cambodia and Kenya are the most frequently observed (in seven out of ten) warehouse locations in the non-dominated solutions. However, when the pre-positioning network is expanded to four warehouses, the benchmark solution keeps Denmark, Hong Kong and Kenya warehouses open and add Honduras as the fourth location. Cambodia and Kenya, on the other hand, are the most frequent warehouse locations observed in the non-dominated solution set for $N = 4$. Thus, since the same four-warehouse network is optimal for benchmark case we can conclude that Denmark, Hong Kong, Kenya and Honduras are the best four warehouse configuration. For $N = 5$, the benchmark solution keeps the four locations obtained in the benchmark solution for $N = 4$ open, and adds Germany as the fifth warehouse. The non-dominated solutions in this group again suggests Cambodia and Kenya as the most popular warehouses as reported in Table 4.

Table 3 Optimal warehouse locations for each benchmark solution

Cambodia	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
		×			×			×				*3*
		×		×	×			×				*4*
		×	×	×	×			×				*5*

Although the consideration of all three objectives together does not alter the locations for the optimal four-warehouse network, it has an impact on the allocation of relief items. We can clearly observe in Table 5 the shift of water supplies from Denmark to Kenya with the consideration of maximum *water delivery time* in the mathematical model.

4.3 Discussion

As stated in the previous subsection, we find the optimal four-warehouse network as Honduras Denmark, Kenya and Hong Kong. Figure 3 illustrates all candidate and selected warehouse locations. In the study Bozkurt and Duran (2012), also suggest the Kenya warehouse as a strong candidate for the fourth location with respect to the data from 2006 to 2010. However, their optimal network structure includes Panama, Kenya, India and Cambodia warehouses. Even though Panama – Honduras and Hong Kong – Cambodia warehouses are close, we propose the Denmark warehouse rather than the India warehouse location. Moreover, we find that the Kenya warehouse should be the largest warehouse in the network (carrying approximately 35% of all tents and 39–44% of all relief items other than tents) and the other three should be in similar sizes in contrary to the results in Bozkurt and Duran (2012) where Kenya warehouse is suggested to be the smallest and the Cambodia to be the largest.

Table 4 Optimal warehouse locations for each non-dominated solution

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	Germany	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
1	×				×		×						*3*
2	×	×						×					*3*
3					×	×			×				*3*
4	×	×							×				*3*
5	×								×		×		*3*
6	×			×					×				*3*
7								×	×			×	*3*
8	×	×						×					*3*
9			×			×			×				*3*
10	×	×							×				*3*
11	×				×			×	×				*4*
12	×						×	×	×				*4*
13	×			×					×			×	*4*
14	×						×		×			×	*4*
15	×		×			×			×				*4*
16	×				×	×		×	×				*5*
17	×	×		×	×				×				*5*
18	×	×				×		×	×				*5*
19	×				×	×		×	×				*5*
20	×	×	×					×	×				*5*
21	×				×		×		×		×		*5*
22	×	×	×		×				×			×	*6*
23	×				×	×		×	×			×	*6*
24	×	×	×		×			×	×				*6*
25	×	×			×			×	×			×	*6*
26	×	×		×				×		×	×		*6*
27	×	×	×							×	×	×	*6*
Frequency	24	12	6	4	11	7	4	13	22	2	4	7	

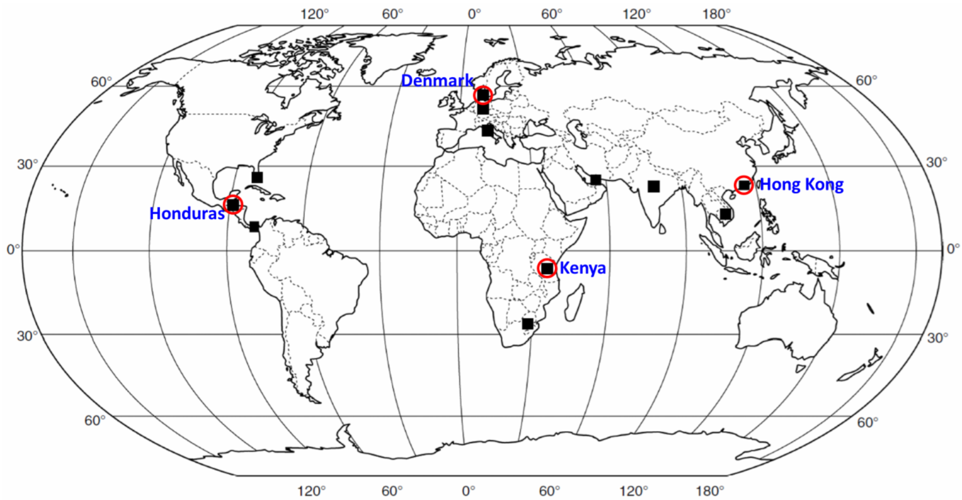
The choice of Kenya as a pre-positioning warehouse and moreover allocating more relief items to that location than any other one has strong results. When we note that our mathematical model considers demand for relief supplies caused by only sudden-onset natural disasters, namely the earthquakes, windstorms (hurricanes, cyclones, storms, tornadoes, tropical storms, and typhoons) and floods but not the droughts, the importance of our Kenya suggestion becomes stronger. Kenya warehouse suggestion by our model can be validated by the following information. According to GFDRR (2016), the most common disasters in Africa are hydro-meteorological or climatological (floods, droughts, and cyclones and storms) and since 1970 Africa had to deal with 750 flood events, 55% of which have taken place in the last decade alone. Thus, the increased flood events in the most recent decade data result in the selection of Kenya location with high inventory levels. However, it should also be kept in mind that, the protection of the inventory and humanitarian actions is at least as important as the location selection decision. In case of Kenya, regarding the risks of natural disasters that may affect a higher proportion the region, preventive and protective measures must be taken in advance. This requires a comprehensive investigation and risk assessment analysis of the possible sites in the selected region to define overall risks and establish ways to mitigate them.

Table 5 Allocation of relief items to warehouses

Solution #	*Optimal locations*	*Relief items*						
		Cold tent	*Hot tent*	*Household utensils*	*Medical relief items*	*Hygiene sets*	*Sanitation sets*	*Water*
B3	Denmark	26%	24%	30%	25%	25%	27%	25%
	Hong Kong	32%	33%	30%	29%	30%	29%	29%
	Kenya	42%	43%	40%	46%	45%	44%	46%
3	Honduras	37%	30%	24%	32%	35%	26%	25%
	Hong Kong	23%	24%	23%	19%	17%	22%	17%
	Kenya	40%	46%	53%	49%	48%	52%	58%
B4	Denmark	21%	21%	17%	16%	17%	16%	*19%*
	Honduras	22%	22%	24%	23%	24%	20%	19%
	Hong Kong	23%	21%	19%	18%	18%	21%	21%
	Kenya	35%	36%	39%	44%	41%	44%	*41%*
15	Denmark	22%	21%	18%	16%	17%	16%	*16%*
	Honduras	22%	24%	23%	22%	23%	22%	21%
	Cambodia	21%	23%	20%	17%	17%	20%	19%
	Kenya	35%	32%	35%	45%	43%	42%	*44%*

We also want to note that, in order to understand the trade-off relation between the objective function values, we have used the 27 non-dominated solutions presented in Table 1. All pairwise correlations are found while keeping the weight of the third objective fixed. According to the obtained results, for all three pairs of the objectives (z_1–z_2, z_1–z_3, and z_2–z_3), we have observed that as the weight of the excluded objective which is not in the pair increases (or the total weight of the paired objectives decreases), the correlation between the paired objective values increases from strong negative to strong positive. In other words, while there is enough weight reserved for paired objectives, they move in opposite directions, and on the contrary while there is a small weight to be shared by these objectives, they move in the same direction, because of the pressure by the weight given to the excluded objective.

Figure 3 Suggested locations for pre-positioning warehouses (see online version for colours)



4.4 Sensitivity analysis

In order to measure the sensitivity of our solutions to the demand uncertainty, we also carry out several experiments for different realisations of demand. In particular for each $N = \{3, 4, 5, 6\}$, we run our mathematical model for d'_{jer} values scaled by 0.7, 0.8, 0.9, 1.1, 1.2, and 1.3. In other words, assuming as the original d'_{jer} value used in previous section as the base case, we solved the model for smaller and larger demand values and evaluated solutions. To evaluate the effect of opening additional warehouses, for each demand value, we solve the 67 instances (for different weights) for all values of N, yielding a total of 268 solutions per a particular demand value. Next, we eliminated the dominated solutions among the 268 solutions. Finally, we ended up with 36, 48, 36, 24, 32, 28 non-dominated solutions for 0.7, 0.8, 0.9, 1.1, 1.2, 1.3 multiples of demand, respectively.

Tables 6–10 summarise the frequencies of warehouse locations observed in the optimal non-dominated solutions for each demand value and N. Tables 11–22 report detailed results in terms of objective function vales, opened warehouses for all non-dominated solutions.

Results for $N = 3$ in Table 6 reveal that Cambodia, Denmark, and Kenya are the most frequent warehouse locations among all demand realisations. Similarly, for $N = 4$, Cambodia, Honduras, Hong Kong, and Kenya are the most popular locations followed by Denmark and Italy. The aggregate frequency results in Table 10 report Kenya (1st rank with a ratio of 17.62%), Cambodia (2nd rank with a ratio of 16.26%), Honduras (3rd rank with a ratio of 12.10%), and finally Denmark (4th rank with a ratio of 10.55%) as the top four warehouse locations. Considering Cambodia Hong Kong is relatively close to Cambodia, the sensitivity analysis results increased our confidence to our suggestion and the idea of opening Denmark warehouse as the fourth location.

Table 6 Frequency of optimal warehouse locations for all non-dominated solutions of each demand value for $N = 3$

Demand/solution	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*
0.70	7	3	4	1	5	2	1	1	8	0	1	3
0.80	7	2	4	2	1	1	0	3	9	1	0	0
0.90	4	2	4	1	5	3	0	1	7	0	0	0
1.00	7	4	1	1	2	2	1	3	7	0	1	1
1.10	3	2	2	0	3	2	1	0	4	0	1	0
1.20	4	2	7	0	2	2	0	0	6	1	0	0
1.30	4	1	3	1	2	2	0	3	5	2	1	0
Frequency	36	16	25	6	20	14	3	11	46	4	4	4
Ratio	19.05%	8.47%	13.23%	3.17%	10.58%	7.41%	1.59%	5.82%	24.34%	2.12%	2.12%	2.12%

Table 7 Frequency of optimal warehouse locations for all non-dominated solutions of each demand value for $N = 4$

Demand/solution	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*
0.70	3	0	1	1	6	4	1	6	7	1	1	1
0.80	8	5	4	1	6	5	0	4	9	0	1	1
0.90	7	2	3	0	7	1	1	0	7	0	1	3
1.00	5	0	1	1	1	1	2	2	5	0	0	2
1.10	3	0	2	1	5	3	1	0	6	1	1	1
1.20	3	1	4	0	3	5	2	3	6	1	0	0
1.30	7	2	4	4	3	4	0	4	5	0	3	0
Frequency	36	10	19	8	31	23	7	19	45	3	7	8
Ratio	16.67%	4.63%	8.80%	3.70%	14.35%	10.65%	3.24%	8.80%	20.83%	1.39%	3.24%	3.70%

Table 8 Frequency of optimal warehouse locations for all non-dominated solutions of each demand value for $N = 5$

Demand/solution	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*
0.70	5	2	4	1	6	4	1	3	5	1	2	2
0.80	7	5	5	2	5	7	4	6	11	3	4	1
0.90	8	3	4	0	8	4	0	3	7	0	1	2
1.00	6	3	1	1	4	3	1	4	6	0	1	0
1.10	7	6	4	4	1	2	1	2	3	0	2	3
1.20	5	3	3	3	7	4	0	8	8	1	1	2
1.30	8	6	4	2	6	2	0	4	5	0	2	1
Frequency	46	28	25	13	37	26	7	30	45	5	13	11
Ratio	16.08%	9.79%	8.74%	4.55%	12.94%	9.09%	2.45%	10.49%	15.73%	1.75%	4.55%	3.85%

Table 9 Frequency of optimal warehouse locations for all non-dominated solutions of each demand value for $N = 6$

Demand/solution	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*
0.70	9	6	6	2	8	5	2	4	9	2	4	3
0.80	12	8	14	5	8	7	3	8	12	3	4	6
0.90	8	2	7	4	7	8	2	8	11	3	2	4
1.00	6	5	3	1	4	1	0	4	4	2	2	4
1.10	5	2	4	1	4	3	1	3	4	0	1	2
1.20	8	5	5	5	6	2	1	4	5	1	3	3
1.30	3	1	1	1	1	2	0	3	2	1	1	2
Frequency	51	29	40	19	38	28	9	34	47	12	17	24
Ratio	14.66%	8.33%	11.49%	5.46%	10.92%	8.05%	2.59%	9.77%	13.51%	3.45%	4.89%	6.90%

Table 10 Frequency of optimal warehouse locations for all non-dominated solutions of each demand value summed for all values of $N = 3, 4, 5, 6$

Demand/solution	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*
0.70	23	11	15	5	24	14	4	14	28	4	8	8
0.80	34	20	27	10	20	20	7	21	41	7	9	8
0.90	27	9	18	5	27	16	3	12	32	3	4	9
1.00	24	12	6	4	11	7	4	13	22	2	4	7
1.10	18	10	12	6	13	10	4	5	17	1	5	6
1.20	20	11	19	8	18	13	3	15	25	4	4	5
1.30	22	10	12	8	12	10	0	14	17	3	7	3
Frequency	168	83	109	46	125	90	25	94	182	24	41	46
Ratio	16.26%	8.03%	10.55%	4.45%	12.10%	8.71%	2.42%	9.10%	17.62%	2.32%	3.97%	4.45%

Table 11 Objective function values and weights for the non-dominated solutions for demand * 0.7

#	N	Objective function term weights			Objective function term values		
		w_1	w_2	w_3	z_1	z_2	z_3
1	3	0.5	0.4	0.1	69,914.53	333.83	391.92
2	3	0.4	0.5	0.1	72,121.75	332.59	387.79
3	3	0.8	0	0.2	70,040.49	332.87	388.52
4	3	0.5	0.2	0.3	70,800.13	332.65	387.50
5	3	0.6	0	0.4	72,475.41	332.97	386.91
6	3	0.4	0.2	0.4	74,417.00	339.49	386.05
7	3	0.1	0.4	0.5	22,566.03	332.55	394.64
8	3	0.4	0	0.6	74,544.66	3609.94	385.63
9	3	0.3	0	0.7	69,020.07	360.59	387.29
10	3	0.1	0.2	0.7	74,975.43	332.90	386.75
11	3	0.1	0.1	0.8	25,739.10	332.61	391.97
12	3	0.1	0	0.9	73,247.37	335.17	386.41
13	4	0.2	0.6	0.2	60,649.81	332.97	391.29
14	4	0.5	0.1	0.4	65,713.81	332.73	389.44
15	4	0.2	0.4	0.4	66,103.57	332.75	388.45
16	4	0.2	0.3	0.5	74,575.75	332.98	387.19
17	4	0.1	0.4	0.5	22,277.36	332.54	394.17
18	4	0.1	0.3	0.6	73,215.32	332.65	387.29
19	4	0.1	0.2	0.7	75,174.83	332.54	398.28
20	4	0.1	0	0.9	26,136.65	332.57	391.47
21	5	0.3	0.5	0.2	58,096.67	332.80	390.69
22	5	0.6	0	0.4	65,294.38	332.89	387.36
23	5	0.1	0.5	0.4	71,936.13	332.64	387.22
24	5	0.1	0.4	0.5	22,529.52	332.53	394.22
25	5	0.3	0.1	0.6	64,204.80	332.67	388.20
26	5	0.1	0.1	0.8	25,307.09	332.55	391.86
27	6	0	0.8	0.2	76,153.61	332.55	388.22
28	6	0.5	0.2	0.3	70,634.77	332.71	388.98
29	6	0.4	0.3	0.3	62,034.35	332.70	389.10
30	6	0.1	0.4	0.5	72,554.26	332.68	387.64
31	6	0.2	0.2	0.6	62,780.20	333.02	388.97
32	6	0.3	0	0.7	66,785.44	332.72	387.61
33	6	0.1	0.2	0.7	24,073.18	332.54	392.75
34	6	0.2	0	0.8	74,006.02	351.55	387.38
35	6	0.1	0.1	0.8	25,314.04	332.55	391.86
36	6	0.1	0	0.9	76,885.99	437.27	387.26

Table 12 Optimal warehouse locations for each non-dominated solution for demand * 0.7

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
1			×										3
2			×		×				×				3
3	×		×						×				3
4				×	×				×				3
5			×		×				×				3
6					×	×			×				3
7	×						×					×	3
8	×	×							×				3
9	×	×							×				3
10	×	×										×	3
11	×										×	×	3
12	×				×			×					3
13			×			×			×				4
14			×			×		×	×				4
15					×	×		×	×				4
16					×	×		×	×				4
17	×				×					×		×	4
18					×	×		×	×				4
19	×			×	×				×				4
20	×							×	×		×		4
21					×		×	×	×				5
22	×	×	×								×	×	5
23	×	×		×	×				×				5
24			×		×	×		×	×				5
25	×				×				×	×	×		5
26	×		×		×	×		×					5
27			×		×	×		×	×				6
28	×				×	×	×		×			×	6
29	×		×		×	×			×	×			6
30	×	×	×		×			×	×				6
31	×	×	×					×	×		×		6
32		×			×	×		×	×		×		6
33	×	×			×	×			×			×	6
34	×				×		×	×	×		×		6
35	×	×	×		×				×	×			6
36	×		×	×	×	×			×				6
Frequency	23	11	15	5	24	14	4	14	28	4	8	8	

Table 13 Objective function values and weights for the non-dominated solutions for demand * 0.8

#	N	*Objective function term weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
1	3	0.10	0.80	0.10	31,329.74	332.60	397.02
2	3	0.10	0.70	0.20	24,503.11	332.62	397.93
3	3	0.50	0.20	0.30	73,757.72	332.54	386.44
4	3	0.50	0.10	0.40	73,724.91	333.64	387.21
5	3	0.20	0.40	0.40	64,076.83	332.85	389.88
6	3	0.20	0.30	0.50	72,852.64	332.56	390.42
7	3	0.40	0.00	0.60	70,062.45	349.27	386.67
8	3	0.20	0.20	0.60	69,114.31	332.70	393.47
9	3	0.20	0.10	0.70	69,915.18	332.80	387.65
10	3	0.10	0.10	0.80	75,580.10	332.53	386.47
11	4	0.10	0.90	0.00	22,590.36	332.55	398.25
12	4	0.70	0.10	0.20	72,932.11	345.58	387.63
13	4	0.40	0.40	0.20	74,162.79	332.69	386.98
14	4	0.40	0.30	0.30	73,962.48	332.89	387.18
15	4	0.40	0.20	0.40	69,728.63	332.71	387.67
16	4	0.20	0.40	0.40	73,635.64	332.68	387.79
17	4	0.10	0.50	0.40	21,617.51	332.58	395.31
18	4	0.20	0.20	0.60	65,023.12	333.51	392.31
19	4	0.10	0.30	0.60	22,881.79	332.55	393.65
20	4	0.20	0.10	0.70	75,759.42	332.72	386.42
21	4	0.33	0.33	0.33	66,132.81	332.60	388.17
22	5	0.30	0.50	0.20	57,693.70	332.74	391.74
23	5	0.20	0.50	0.30	61,841.64	332.61	397.62
24	5	0.60	0.00	0.40	72,786.99	343.49	386.82
25	5	0.30	0.30	0.40	60,469.95	332.95	389.84
26	5	0.10	0.50	0.40	72,569.55	332.59	387.09
27	5	0.00	0.60	0.40	78,822.70	332.59	397.34
28	5	0.50	0.00	0.50	67,211.41	333.04	388.74
29	5	0.40	0.10	0.50	67,350.61	332.99	389.44
30	5	0.00	0.50	0.50	78,822.44	332.58	397.52
31	5	0.30	0.10	0.60	66,328.38	333.01	389.31
32	5	0.10	0.20	0.70	71,886.94	332.83	388.07
33	5	0.33	0.33	0.33	70,551.05	332.77	388.27
34	6	0.20	0.80	0.00	62,046.90	332.65	405.09
35	6	0.10	0.90	0.00	67,092.72	332.60	405.59
36	6	0.20	0.70	0.10	59,308.85	332.71	401.82

Table 13 Objective function values and weights for the non-dominated solutions for demand * 0.8 (continued)

#	N	*Objective function term weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
37	6	0.00	0.90	0.10	78,158.82	332.50	385.06
38	6	0.30	0.50	0.20	55,856.52	332.93	401.18
39	6	0.20	0.60	0.20	54,022.50	333.85	398.99
40	6	0.50	0.20	0.30	68,650.58	333.01	388.69
41	6	0.00	0.70	0.30	71,986.11	332.63	402.96
42	6	0.50	0.10	0.40	63,898.30	332.73	389.02
43	6	0.30	0.30	0.40	62,011.97	333.39	390.02
44	6	0.20	0.40	0.40	61,366.97	332.71	399.96
45	6	0.40	0.10	0.50	69,054.79	332.74	387.19
46	6	0.30	0.20	0.50	58,593.92	333.38	393.78
47	6	0.10	0.30	0.60	72,949.87	332.69	387.54
48	6	0.33	0.33	0.33	73,798.78	332.64	386.87

Table 14 Optimal warehouse locations for each non-dominated solution for demand * 0.8

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
1				×		×			×				3
2	×							×	×				3
3	×								×	×			3
4	×	×	×										3
5			×		×				×				3
6	×							×	×				3
7	×		×						×				3
8	×	×							×				3
9	×			×					×				3
10			×					×	×				3
11			×		×	×			×				4
12	×				×	×			×				4
13	×	×	×	×									4
14	×	×	×						×				4
15					×	×		×	×				4
16	×	×				×			×				4
17	×	×						×				×	4
18	×	×			×				×				4
19					×	×		×	×				4

Table 14 Optimal warehouse locations for each non-dominated solution for demand * 0.8 (continued)

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
20	×		×					×	×				4
21	×				×				×		×		4
22	×	×					×		×		×		5
23	×			×				×	×			×	5
24			×			×	×		×	×			5
25			×		×	×		×	×				5
26	×	×	×						×		×		5
27	×	×				×			×		×		5
28	×						×	×	×		×		5
29			×		×	×		×	×				5
30		×		×		×	×		×				5
31	×	×			×			×		×			5
32	×				×	×			×	×			5
33			×		×	×		×	×				5
34	×	×	×	×	×				×				6
35		×	×		×			×	×		×		6
36	×	×	×			×		×	×				6
37			×		×		×		×		×	×	6
38	×		×		×	×		×	×				6
39	×	×	×					×	×			×	6
40	×		×		×	×		×	×				6
41	×	×							×	×	×	×	6
42	×	×	×	×	×	×							6
43	×		×	×	×				×			×	6
44		×	×			×		×	×			×	6
45	×		×		×	×		×	×				6
46	×		×			×	×	×		×			6
47	×	×	×	×							×	×	6
48	×		×	×			×		×	×			6
Frequency	34	20	27	10	20	20	7	21	41	7	9	8	

Table 15 Objective function values and weights for the non-dominated solutions for demand * 0.9

#	N	*Objective function term weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
1	3	0.70	0.10	0.20	73,041.78	367.71	385.88
2	3	0.20	0.60	0.20	68,494.02	332.55	399.78
3	3	0.10	0.70	0.20	65,861.90	332.61	389.25
4	3	0.20	0.50	0.30	75,355.17	332.66	387.21
5	3	0.30	0.20	0.50	70,682.47	332.58	387.47
6	3	0.10	0.30	0.60	23,650.25	332.63	393.83
7	3	0.30	0.00	0.70	75,468.68	350.95	386.63
8	3	0.20	0.10	0.70	76,172.26	332.88	386.84
9	3	0.10	0.20	0.70	26,453.66	332.63	393.12
10	4	0.20	0.60	0.20	75,820.23	332.69	386.64
11	4	0.60	0.10	0.30	72,536.82	340.29	386.68
12	4	0.60	0.00	0.40	68,999.42	332.66	387.09
13	4	0.40	0.10	0.50	67,027.95	332.89	389.05
14	4	0.20	0.10	0.70	76,057.92	332.97	386.56
15	4	0.10	0.20	0.70	76,299.81	332.58	385.88
16	4	0.20	0.00	0.80	75,788.61	334.29	386.69
17	4	0.10	0.10	0.80	25,752.29	332.62	392.69
18	5	0.30	0.50	0.20	56,672.04	332.63	389.98
19	5	0.00	0.80	0.20	78,814.11	332.58	397.76
20	5	0.30	0.20	0.50	74,047.83	332.76	389.30
21	5	0.20	0.30	0.50	75,548.95	332.73	387.57
22	5	0.10	0.40	0.50	22,375.24	332.59	394.33
23	5	0.30	0.00	0.70	68,883.86	332.92	386.79
24	5	0.00	0.30	0.70	78,821.06	332.58	397.21
25	5	0.33	0.33	0.33	73,526.01	332.86	388.47
26	6	0.40	0.50	0.10	53,359.83	333.11	401.12
27	6	0.30	0.60	0.10	63,252.33	332.93	390.97
28	6	0.10	0.80	0.10	68,413.11	332.64	396.27
29	6	0.60	0.10	0.30	73,727.48	352.94	386.27
30	6	0.20	0.50	0.30	60,341.95	332.72	399.49
31	6	0.20	0.40	0.40	71,277.75	332.81	387.94
32	6	0.20	0.30	0.50	66,201.86	332.84	399.29
33	6	0.20	0.20	0.60	71,776.87	332.91	387.35
34	6	0.00	0.30	0.70	78,821.16	332.58	398.97
35	6	0.20	0.00	0.80	72,571.40	332.64	386.47
36	6	0.10	0.10	0.80	74,212.45	332.60	386.91

Table 16 Optimal warehouse locations for each non-dominated solution for demand * 0.9

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
1	×							×	×				3
2					×	×			×				3
3	×				×				×				3
4			×		×				×				3
5					×	×			×				3
6	×	×		×									3
7			×			×			×				3
8			×		×				×				3
9	×	×	×										3
10			×		×	×			×				4
11	×				×				×			×	4
12	×				×				×			×	4
13	×	×			×						×		4
14	×				×		×		×				4
15	×				×				×			×	4
16	×		×		×				×				4
17	×	×	×						×				4
18	×		×		×			×	×				5
19	×				×	×		×	×				5
20	×	×			×			×	×				5
21	×		×		×	×			×				5
22	×		×		×	×						×	5
23	×	×	×		×				×				5
24	×				×	×			×		×		5
25	×	×			×				×			×	5
26	×	×	×	×				×	×				6
27	×		×		×	×		×	×				6
28	×				×	×		×	×			×	6
29	×				×	×	×		×			×	6
30	×		×	×	×	×			×				6
31	×		×	×	×			×	×				6
32	×		×		×	×		×	×				6
33				×			×		×	×	×	×	6
34			×		×	×		×	×	×			6
35	×		×			×		×	×	×			6
36		×				×		×	×		×	×	6
Frequency	27	9	18	5	27	16	3	12	32	3	4	9	

Table 17 Objective function values and weights for the non-dominated solutions for demand * 1.1

#	N	*Objective function term weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
1	3	0.50	0.30	0.20	65,236.69	333.03	390.28
2	3	0.70	0.00	0.30	69,086.22	332.99	387.71
3	3	0.40	0.10	0.50	75,311.22	332.99	387.09
4	3	0.20	0.10	0.70	21,365.82	332.54	395.52
5	3	0.10	0.10	0.80	26,011.68	332.54	391.85
6	3	0.33	0.33	0.33	69,098.49	332.76	388.19
7	4	0.10	0.70	0.20	20,157.97	332.55	397.20
8	4	0.70	0.00	0.30	69,677.18	333.63	391.67
9	4	0.50	0.20	0.30	74,395.82	332.63	386.90
10	4	0.60	0.00	0.40	72,691.58	332.63	387.18
11	4	0.40	0.00	0.60	72,460.05	333.52	387.23
12	4	0.10	0.20	0.70	23,988.22	332.55	392.75
13	5	0.10	0.80	0.10	19,946.11	332.56	398.29
14	5	0.60	0.10	0.30	67,389.17	333.28	392.16
15	5	0.00	0.70	0.30	78,820.12	332.57	397.17
16	5	0.60	0.00	0.40	74,380.05	333.48	388.94
17	5	0.50	0.00	0.50	73,242.70	335.79	388.28
18	5	0.40	0.00	0.60	68,177.80	333.98	388.34
19	5	0.20	0.00	0.80	76,882.50	559.90	387.25
20	6	0.10	0.90	0.00	19,798.61	332.54	398.98
21	6	0.40	0.10	0.50	67,637.61	333.44	389.07
22	6	0.40	0.00	0.60	68,514.89	332.62	386.70
23	6	0.10	0.30	0.60	22,899.24	332.55	393.65
24	6	0.10	0.20	0.70	23,942.05	332.55	392.86

Table 18 Optimal warehouse locations for each non-dominated solution for demand * 1.1

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
1		×							×		×		3
2	×		×		×								3
3	×	×	×										3
4					×	×			×				3
5	×						×		×				3
6					×	×			×				3
7	×		×		×				×				4

Table 18 Optimal warehouse locations for each non-dominated solution for demand * 1.1 (continued)

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
8	×				×	×			×				4
9						×			×	×		×	4
10					×		×		×		×		4
11	×			×	×				×				4
12			×		×	×			×				4
13	×	×	×			×			×				5
14	×	×						×	×		×		5
15	×				×		×	×	×				5
16	×	×		×							×	×	5
17	×	×	×	×								×	5
18	×	×	×	×								×	5
19	×	×	×	×		×							5
20	×				×	×		×	×		×		6
21	×		×		×	×		×	×				6
22	×	×	×	×	×							×	6
23	×	×	×				×		×			×	6
24	×		×		×	×		×	×				6
Frequency	18	10	12	6	13	10	4	5	17	1	5	6	

Table 19 Objective function values and weights for the non-dominated solutions for demand * 1.2

#	*N*	*Objective function term weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
1	3	0.10	0.60	0.30	20,909.92	332.53	396.20
2	3	0.50	0.10	0.40	74,583.89	334.72	386.44
3	3	0.30	0.30	0.40	67,558.62	333.23	388.91
4	3	0.20	0.30	0.50	74,802.22	332.64	387.17
5	3	0.10	0.40	0.50	22,614.65	332.56	394.18
6	3	0.40	0.00	0.60	73,688.17	332.64	386.89
7	3	0.20	0.10	0.70	72,415.71	332.92	388.41
8	3	0.10	0.00	0.90	29,683.77	332.80	392.50
9	4	0.50	0.10	0.40	72,049.32	332.78	387.33
10	4	0.30	0.30	0.40	66,898.30	333.39	388.44
11	4	0.30	0.20	0.50	70,046.35	332.78	388.87

Table 19 Objective function values and weights for the non-dominated solutions for demand * 1.2 (continued)

#	N	*Objective function term weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
12	4	0.10	0.20	0.70	24,333.25	332.56	392.75
13	4	0.10	0.10	0.80	25,353.18	332.55	391.86
14	4	0.10	0.00	0.90	26,396.28	332.72	391.44
15	4	0.33	0.33	0.33	70,009.18	332.72	389.44
16	5	0.10	0.90	0.00	25,487.30	332.60	399.17
17	5	0.00	0.90	0.10	50,053.53	333.00	396.53
18	5	0.40	0.30	0.30	66,440.80	333.59	392.66
19	5	0.10	0.60	0.30	71,239.97	333.13	392.04
20	5	0.00	0.70	0.30	78,821.35	332.58	397.50
21	5	0.40	0.20	0.40	73,102.91	333.02	387.98
22	5	0.10	0.50	0.40	70,305.94	333.36	395.64
23	5	0.40	0.00	0.60	75,071.11	332.68	387.26
24	5	0.00	0.40	0.60	78,829.05	332.61	397.19
25	6	0.50	0.40	0.10	56,311.61	332.86	391.85
26	6	0.50	0.30	0.20	74,768.40	332.55	386.44
27	6	0.40	0.40	0.20	57,640.08	332.78	391.49
28	6	0.20	0.50	0.30	66,844.10	333.06	390.49
29	6	0.10	0.50	0.40	21,404.84	332.55	395.26
30	6	0.30	0.20	0.50	71,340.44	333.06	389.86
31	6	0.30	0.00	0.70	73,833.99	332.95	387.45
32	6	0.10	0.10	0.80	25,563.90	332.59	391.92

Table 20 Optimal warehouse locations for each non-dominated solution for demand * 1.2

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
1			×		×				×				3
2			×			×			×				3
3			×		×				×				3
4			×			×			×				3
5	×		×						×				3
6	×	×	×										3
7	×								×	×			3
8	×	×	×										3
9			×		×	×			×				4
10	×		×				×		×				4

Table 20 Optimal warehouse locations for each non-dominated solution for demand * 1.2 (continued)

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
11			×		×	×			×				4
12	×					×		×	×				4
13					×	×		×	×				4
14		×				×			×	×			4
15	×		×				×	×					4
16			×		×	×		×	×				5
17	×			×	×			×	×				5
18	×	×	×		×						×		5
19					×	×		×	×			×	5
20	×	×		×				×	×				5
21	×	×				×		×	×				5
22	×				×			×	×	×			5
23			×		×	×		×	×				5
24				×	×			×	×			×	5
25	×	×	×	×	×	×							6
26	×			×	×			×	×		×		6
27	×		×		×			×	×			×	6
28	×	×	×	×	×	×							6
29	×	×	×		×		×		×				6
30	×	×	×		×			×	×				6
31	×			×				×	×		×	×	6
32	×	×		×						×	×	×	6
Frequency	20	11	19	8	18	13	3	15	25	4	4	5	

Table 21 Objective function values and weights for the non-dominated solutions for demand * 1.3

#	*N*	*Objective function term weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
1	3	0.10	0.80	0.10	73,561.56	332.52	402.58
2	3	0.20	0.60	0.20	69,364.10	332.80	389.20
3	3	0.40	0.20	0.40	75,349.70	333.91	386.41
4	3	0.30	0.30	0.40	72,244.44	333.18	388.26
5	3	0.20	0.40	0.40	69,330.43	332.85	388.91
6	3	0.40	0.00	0.60	74,030.02	333.23	387.70

Table 21 Objective function values and weights for the non-dominated solutions for demand * 1.3 (continued)

#	N	*Objective function term weights*			*Objective function term values*		
		w_1	w_2	w_3	z_1	z_2	z_3
7	3	0.30	0.10	0.60	74,753.07	332.57	386.73
8	3	0.10	0.30	0.60	23,179.08	332.54	393.63
9	4	0.30	0.70	0.00	64,641.93	332.82	403.59
10	4	0.10	0.90	0.00	70,648.94	332.58	403.20
11	4	0.00	0.80	0.20	74,072.57	332.63	399.51
12	4	0.40	0.10	0.50	73,446.20	340.02	387.12
13	4	0.20	0.30	0.50	65,207.94	332.83	389.13
14	4	0.20	0.10	0.70	75,432.21	332.55	386.91
15	4	0.10	0.20	0.70	74,457.87	332.73	387.56
16	4	0.20	0.00	0.80	77,867.59	424.67	386.60
17	4	0.33	0.33	0.33	70,347.78	332.76	398.46
18	5	0.10	0.80	0.10	19,943.30	332.55	398.27
19	5	0.50	0.20	0.30	74,975.46	333.05	388.95
20	5	0.30	0.40	0.30	64,056.43	332.69	391.95
21	5	0.20	0.50	0.30	66,974.20	332.78	389.14
22	5	0.10	0.50	0.40	21,572.89	332.58	395.32
23	5	0.40	0.10	0.50	74,447.69	333.17	388.03
24	5	0.10	0.40	0.50	22,420.49	332.57	394.23
25	5	0.40	0.00	0.60	75,502.61	343.10	387.07
26	6	0.10	0.40	0.50	73,725.60	332.57	388.91
27	6	0.30	0.00	0.70	70,918.02	332.78	386.50
28	6	0.10	0.10	0.80	25,759.84	332.61	391.92

Table 22 Optimal warehouse locations for each non-dominated solution for demand * 1.3

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
1	×								×	×			3
2				×		×			×				3
3	×							×	×				3
4	×	×						×					3
5	×		×							×			3
6					×	×		×					3
7			×						×		×		3
8			×		×				×				3

Table 22 Optimal warehouse locations for each non-dominated solution for demand * 1.3 (continued)

Solution #	*Cambodia*	*USA, Miami*	*Denmark*	*Germany*	*Honduras*	*Hong Kong*	*India*	*Italy*	*Kenya*	*Panama*	*South Africa*	*UAE, Dubai*	*N*
9			×			×		×	×				4
10	×				×	×			×				4
11			×	×		×					×		4
12	×				×			×	×				4
13	×	×	×	×									4
14	×							×	×		×		4
15	×				×	×			×				4
16	×	×		×							×		4
17	×		×	×				×					4
18	×	×	×	×					×				5
19	×				×	×		×	×				5
20	×				×	×		×	×				5
21	×	×		×	×				×				5
22	×	×	×					×				×	5
23	×	×	×		×						×		5
24	×	×			×			×			×		5
25	×	×	×		×				×				5
26	×					×		×	×		×	×	6
27	×		×			×		×	×			×	6
28	×	×		×	×			×		×			6
Frequency	22	10	12	8	12	10	0	14	17	3	7	3	

5 Conclusions

In this study, we consider the pre-positioning strategy for humanitarian response to disasters by a multi-objective mathematical model developed specifically for CARE International. In accordance to the work of Duran et al. (2011), CARE initiate its pre-positioning warehouse network with Panama, Dubai and Cambodia warehouses. It has been a decade since that strategic decision is given and we revisit the same problem with a multi-objective approach and a new decade of disaster data to see if an update is needed in the initial network structure.

With similar data collection methodology and mathematical modelling techniques to the previous works (Duran et al., 2011; Bozkurt and Duran, 2012), and considering *maximum response time* and *maximum water delivery time* as additional objectives to the *average response time*, we find 17 non-dominated solutions out of 402 solutions. When these non-dominated solutions are examined, the three-warehouse configuration of Honduras – Kenya – Hong Kong and the four-warehouse configuration of Honduras – Denmark – Kenya – Hong Kong are selected as most applicable ones.

Although Bozkurt and Duran (2012) suggested the opening of a new warehouse in Kenya as the fourth pre-positioning warehouse and moving the half of the inventories in Dubai warehouse to Kenya with the usage of 2007–2010 data, when the complete 2007–2016 disaster data is utilised and additional objectives to the average *response time* is considered we cannot suggest the usage of Dubai warehouse anymore. CARE International should open the Kenya warehouse and pre-position 40–46% of all relief items other than tents to this location while starting to operate the Denmark warehouse instead of Dubai warehouse.

Inclusion of the Kenya location as the biggest pre-positioning warehouse to the established three-warehouse configuration is appropriate for CARE International considering the fact that droughts, which are not included in our study, affect over eight million people annually which corresponds to 78% of the total disaster affected population in the continent of Africa (GFDRR, 2016).

Since we take the mean demand to determine the level of the decision variables in this study, in the future works a safety stock with a certain service level may be considered and experimented for the possible fluctuations in demand to see the effect of variability.

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