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Allocation of temporary disaster response facilities under demand uncertainty: An earthquake case study

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ABSTRACT

In this paper, we consider the problem of temporary disaster response facility allocation for temporary or short-term disaster relief operations, propose a solution approach and illustrate it with an earthquake case study in Turkey. A two-stage stochastic program is developed for the solution of the problem to minimize the total distance traveled, the unmet demand and the total number of facilities (considering the potential difficulties to access the facilities), where facility allocation and service decisions are performed in the first and second stages, respectively. An earthquake case study developed by the Prime Ministry Disaster and Emergency Management Authority (mostly referred as AFAD in Turkey) is used to test our model. We use five different scenarios, each representing a different after-disaster situation (i.e., traffic conditions, time etc.), with its respective probability of occurrence, to model the demand uncertainty for relief supplies. We first solve the deterministic model for each scenario, and then, the corresponding stochastic program. In addition to the defined objectives of the model, quality of each solution is analyzed in terms of average walking distance, demand satisfaction rate and average facility utilization.

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1. Introduction

Increases in populations, infrastructure complexities, combined with the fast and unplanned urbanization, also increase the unwanted effects of disasters all around the world. It is noted that even a single disaster might cause losses of thousands of lives and billions of dollars as observed in the Japan Earthquake and Tsunami in 2011, one of the most destructive disasters of recent years (EM-DAT: The International Disaster Database, 2015). As a result of such facts, Disaster Operations Management (DOM) studies gain even more interest recently. Since DOM is about the management of disaster operations, it is one of the areas where operations researchers, both academicians and practitioners, can make contributions by developing solution approaches for the challenging problems in DOM.

Disaster Relief Operations (DRO), representing a subset of general disaster operations, are performed after a disaster to reduce the unwanted effects of the disaster, such as emergency or relief supply distribution to disaster victims to help them satisfy their basic needs. In general, these operations are performed by some kind of governmental or central humanitarian organizations, such as the Federal Emergency Management Agency (FEMA) or the Red Cross. Such organizations usually prepare some action plans to maximize the success of DRO. Nevertheless, even the expertise of such organizations might not be sufficient to properly reduce the unwanted effects of a disaster due to the extraordinary conditions of disasters, since, under such conditions, it might not be possible to perform DRO in a timely manner, especially in metropolitan areas with high infrastructure complexities. As a result, utilizing some so-called local (or distributed) supporting DRO, where possible, in addition to the global (or centralized) ones, might improve the success of these operations significantly. Establishing some localized-facilities to satisfy the basic needs of disaster victims, for instance, might improve the efficiency of the corresponding DRO.

In this paper, we consider the allocation of such local facilities, Temporary Disaster-Response (TDR) facilities as we refer in this study, under demand uncertainty to improve the efficiency of relief supplies distribution operations. A two-stage stochastic-integer programming model is developed for the solution of the problem to minimize the total distance traveled, the unmet demand and the total number of facilities (considering the potential difficulties to access the facilities), where the facility allocation and service decisions are performed in the first and second stages, respectively. Note that the structure of two-stage stochastic programs allows us making some decisions before the realization of a

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future event (disaster, in our case) considering the possible outcomes of the event by utilizing some descriptive scenarios to represent such possible outcomes since the future is usually not known for certain. In particular, we allocate the facilities in the first stage by minimizing the total number of facilities considering the potential difficulties to access the facilities and the expected second stage objective. In the second stage, we then plan the distribution of relief supplies (recourse actions) with minimum total travel distance and unmet commodity (relief supplies) demands. Our model is tested with a real-life earthquake-case study developed by the Prime Ministry Disaster and Emergency Management Authority (AFAD) for a district of Bursa, a metropolitan city in Turkey. We use five different scenarios, each representing a different after-disaster situation (i.e., traffic conditions, time etc.), with its respective probability of occurrence, to model the demand uncertainty for commodities. We present the optimal facility allocations by solving the deterministic model for each scenario as well as the stochastic program and the mean-value problem.

The organization of the paper is as follows. In the next section, a brief literature review is presented. The details of the two-stage stochastic programming model is given in the following section. We then define the case study and present the results. Final remarks are given in the conclusions section.

2. Literature review

Disasters are catastrophic events of extraordinary conditions which cause important losses all around the world. It is thus very important for all nations to develop their solutions to prevent, or at least, to reduce these losses. Management of such efforts, generally referred as Disaster Operations Management (DOM), gains even more attention recently as a result of the increasing impacts of the disasters of recent years. Among others, operations researchers make important contributions to DOM studies by developing solution approaches for the challenging problems in DOM.

Altay and Green in [1], and more recently, of Galindo and Batta in [2] present comprehensive reviews of Operations Research-Management Science (OR-MS) studies in DOM. As presented in these reviews, we can use different classifications to categorize DOM studies, such as classifying them with respect to disaster types, phases of disaster operations etc. With respect to their types, disasters can be classified as natural or technological (human-made) depending on their causes, if they are natural (i.e., earthquakes, floods etc.) or human-made (nuclear power plant failures, power outages etc.) though it is possible, in some cases, a disaster might be a combination of both, such as the Japan Earthquake and Tsunami in 2011 (EM-DAT: The International Disaster Database, 2015). According to [2], more recently, an increase in the number of the studies related to natural disasters is observed compared to the findings of [1]. In terms of the phases of disaster operations, the most straightforward classification is distinguishing them as pre-disaster and post-disaster operations corresponding to the operations to-be-performed before and after the disaster, respectively. Another classification defines four different phases as mitigation, preparedness, response and recovery, which can be defined as, preventing potential disasters or reducing their effects (mitigation), preparing for successfully-handling disasters (preparedness), utilizing available resources for protection and well-being (response) and restoring normal conditions in the long-run (recovery), respectively. A comprehensive categorization of various OR-MS studies with respect to these phases can be found in [1]. Considering such classifications, however, we also note that some studies might be related to more than just one of these phases. For instance, although the facility allocation problem considered in this study mainly involves response operations, it is also related to preparedness. In particular, locating TDR facilities and pre-positioning relief supplies are mainly related to the preparedness phase whereas the distribution operations of the relief supplies are performed in the response phase. Some other examples of such studies involving more than one phase are presented in [3–5,6].

As stated in [2], OR-MS studies about response operations seem to gain more attention recently. Evacuation operations as in [7–15,16] and, as an emerging area, humanitarian relief logistics operations as in [17–32,33] are examples of response-related studies. It is noted that, differently from a general supply chain, in humanitarian relief logistics, it is generally more important to provide relief supplies to disaster victims as soon as possible rather than minimizing some other monetary cost-driven function.

An important research area in humanitarian relief logistics is facility allocation. In a general problem setting, its involvement with different DOM phases (i.e., preparedness and response), makes facility allocation a more challenging problem since it now requires the consideration of stochastic problem parameters, such as demand amount-location, road status-capacity and resource availability.

Different approaches are used to deal with such stochastic problem parameters. Some studies consider the worst-case and the most-likely scenario ([3,5]). In such cases, a deterministic version of the problem corresponding each of these scenarios is solved. In some other studies, stochastic optimization-based solution approaches are used. In particular, such solution approaches are commonly used for solving allocation problems in DOM. Huang et al. [34] use robust optimization for multiple emergency resources allocation with uncertain availability and travel-service times. Fiedrich et al. [35] also consider emergency resources allocations in which disaster location, number of victims and travel time are unknown parameters of the problem. Some studies consider the allocations of particular disaster facilities, such as shelters and some kind of disaster supply facilities. Yazici and Ozbay [36] use stochastic optimization for shelter allocation problem for hurricane evacuation where link capacities are assumed to be stochastic. Murali et al. [37] and Zhu et al. [38] perform local reserve depots allocation with unknown demand. Chan et al. [39] combines a similar depots allocation problem with vehicle routing. Some studies also consider distribution of commodities, such as emergency or relief supplies. Mete and Zabinsky [4], for instance, allocate medical supply facilities with uncertain disaster location, demand and link status. Rawls and Turnquist [29] consider uncertain demand and link status in emergency supplies facilities allocation. In another study of theirs, Rawls and Turnquist [30] also utilize service constraints for a similar problem.

In particular, for solving facility allocation problems in DOM, two-stage stochastic programs are used in several studies as the problem structure allows the utilization of a such framework; i.e., the allocation of facilities is performed in the first stage whereas the second stage usually involves some post-disaster operations, such as providing some kind of service after the disaster as in [23,29,30,40,41]. In [42], the authors consider a distribution network design problem to determine the locations and capacities of the relief distribution points with demand- and network-related uncertainties. In [43], a similar facility allocation problem with risk-aversion is presented. We also consider a facility allocation problem in this study, the allocation of TDR facilities, as referred in this paper, motivated by the fact that, although there are several studies using two-stage stochastic programming for solving facility allocation problems in DOM, according to the best of our knowledge, none of these define their context as the allocation of TDR facilities, representing a special type with its own problem characteristics. In particular, since TDR facilities are designated as a

different type of facility which are supposed to serve disaster victims temporarily, as the name (temporary) suggests, until the arrival of central disaster response units, their allocation requires the consideration of some particular constraints, such as the supply-ratios, safety conditions and service levels to prevent chaotic situations and maximize the efficiency of distribution operations, which, again according to the best of our knowledge, are not considered in previous studies.

3. Methodology

In this section, we present the details of the two-stage stochastic-integer programming model developed for the solution of the problem to minimize the total distance traveled, the unmet demand and the total number of facilities (considering the potential difficulties to access the facilities), where the facility allocation and service decisions are performed in the first and second stages, respectively. In particular, we allocate the facilities in the first stage by minimizing the total number of facilities considering the potential difficulties to access the facilities and the expected second stage objective. In the second stage, we then plan the distribution of relief supplies (recourse actions) with minimum total travel distance and unmet commodity (relief supplies) demands.

Our model includes some other problem constraints in addition to the general ones considered in similar problems as detailed in the following parts of this section. We ensure, for instance, that different commodities are distributed to disaster victims by preserving some certain proportions between each commodity-pair (Eq. (3)). By doing so, we make sure that each disaster victim is able to receive the required amounts of commodities from a single neighborhood. Consideration of such issues might improve the efficiency of DRO significantly by eliminating the possible chaotic situations during relief operations. Setting service limits might also help preventing undesired situations in DRO. We also consider such service level constraints by defining upper-bounds for the number of neighborhoods that a single neighborhood can serve and the number of neighborhoods that can serve a single neighborhood (Eqs. (7) and (8)). Obviously, for successful DRO, ensuring the safety of the commodities in such compact facilities (i.e., TDR facilities) is very crucial by taking possible damages into account, especially in metropolitan areas with high crime rates. A practical solution here is allocating the facilities in relatively safer neighborhoods so that the risk of such damages is decreased. We enforce this condition in the proposed model by not allowing the allocation in particular neighborhoods whose crime rates (safety levels) are higher (lower) than some pre-defined threshold Eq. (13).

Although they are also referred in the text, a list of problem indexes, parameters and variables are presented first in Table 1 for the convenience of the reader. We consider n_C commodities, such as water, meal-ready-to-eat, medical kit etc., that will be required by the victims in the short-term right after the disaster where commodity k has a volume of v_k and weight of w_k. A network of size n_N, representing the affected area, is considered, where the distance between nodes i and j is represented by c_{ij}. We assume a total number of N_T facilities are available, out of which n_i is the maximum number allowed in neighborhood i. A single TDR facility has a volume capacity of V and a weight capacity of W. We further assume that each neighborhood has an associated accessibility parameter, a_i for neighborhood i, a lower number representing a better accessibility. Utilization of such an accessibility parameter allows us to consider the possible difficulties to access the commodities in the TDR facilities in a particular neighborhood, i.e., a neighborhood with a higher infrastructure complexity might have a worse accessibility etc. A demand of $d_{jk}(\xi)$ is assumed for commodity k in neighborhood j for disaster scenario ξ.

Table 1
Indexes, parameters and variables.

i, j	neighborhood, $i, j = 1, \ldots, n_N$
k, p, q	commodity, $k, p, q = 1, \ldots, n_C$
ξ	scenario
c_{ij}	cost (i.e., distance) between neighborhoods i and j
$v_k(w_k)$	unit volume (weight) of commodity k
$V(W)$	volume (weight) capacity of a single facility
r_{pq}	supply-ratio between commodity-pairs p and q
$d_{jk}(\xi)$	demand of commodity k in neighborhood j for disaster scenario ξ
$p(\xi)$	probability of scenario ξ
a_i	accessibility parameter for neighborhood i
n_i	max. num. of facilities allowed in neighborhood i
N_T	total number of facilities available
s_i	safety level in neighborhood i
S_T	safety level threshold
α	max. num. of neighborhoods that a single neighborhood can serve
β	max. num. of neighborhoods that can serve a single neighborhood
λ	scaling factor between the first and second stage objectives
γ	cost (penalty) of each unit of unmet demand
z_i	number of facilities opened in neighborhood i (first stage variable)
$y_{ij}(\xi)$	binary variable representing if neighborhood i serves neighborhood j
$x_{ijk}(\xi)$	commodity k to be supplied from neighborhood i to neighborhood j for scenario ξ
$u_{jk}(\xi)$	unmet demand of commodity k in neighborhood j

In the first stage, before the occurrence of a possible disaster and thus the realization of the demands, the number of TDR facilities z_i in neighborhood i must be decided by considering the accessibility parameter (a_i) of the neighborhood. In other words, we not only minimize the number of facilities, but also consider the potential difficulties to access the commodities in the facilities by multiplying the number of TDR facilities in each neighborhood by the associated accessibility parameter of the neighborhood. Second stage decision variables $x_{ijk}(\xi)$ are defined as the number of commodity k to be supplied by the facilities in neighborhood i for the people in neighborhood j for earthquake scenario ξ. Similarly, binary variables $y_{ij}(\xi)$ are defined as 1 if at least one TDR facility in neighborhood i serve(s) to neighborhood j for earthquake scenario ξ and 0 otherwise. Finally, additional variables $u_{jk}(\xi)$ are defined as the unmet demand of commodity k in neighborhood j. Note that, these variables not only present the commodity demands that cannot be satisfied, but also prevent a possible infeasibility due to a recourse in the stochastic program. We want to minimize the total distance traveled by disaster victims, amount of unmet demand and total number of facilities (considering the potential difficulties to access the facilities). Since the total number of facilities opened must be decided before the realization of the commodity demands (depending on the earthquake scenario), z_i, $\forall\ i$ are defined as the first stage variables whereas $x_{ijk}(\xi)$, $\forall\ i, j, k$, $y_{ij}(\xi)$, $\forall\ i, j$ and $u_{jk}(\xi)$, $\forall\ j, k$ represent the second-stage variables for scenario ξ. We can thus write the objective function of the stochastic program to minimize as

$$\min \lambda \sum_{i=1}^{n_N} a_i z_i + \sum_{\xi} p(\xi) \left[\sum_{i=1}^{n_N} \sum_{j=1}^{n_N} c_{ij} \left(\sum_{k=1}^{n_C} x_{ijk}(\xi) \right) + \sum_{j=1}^{n_N} \sum_{k=1}^{n_C} \gamma u_{jk}(\xi) \right] \quad (1)$$

where λ is a scaling factor, $p(\xi)$ is the probability of scenario ξ and γ is defined as the cost (penalty) for each unit of unmet demand. Eq. (1) is minimized subject to the following constraints. The constraint given by Eq. (2) ensures that the commodity demands are satisfied by the facilities.

$$\sum_{i=1}^{n_N} x_{ijk}(\xi) = d_{jk}(\xi) - u_{jk}(\xi), \quad \forall\ j, k, \xi \tag{2}$$

Eq. (3) defines the supply-ratios between each commodity-pairs. Although a person's daily requirements are already defined (in Table 3), note that Eq. (3) is still required to ensure that the disaster victims in a particular neighborhood receive the amounts proportional to the supply-ratios from a particular neighborhood. For instance, as seen in Table 3, a person's required amount of food is nine times of the person's required amount of medical kit. By employing Eq. (3), we ensure that if a particular neighborhood supplies one unit of medical kit to another neighborhood, it then has to supply exactly nine units of food to the same neighborhood. In other words, without Eq. (3), the disaster victims in a particular neighborhood might receive the required amounts of commodities from different neighborhoods causing an undesired situation.

$$r_{pq}x_{ijp}(\xi) = r_{qp}x_{ijq}(\xi), \quad \forall\ i, j, \quad \forall\ p, q; p \neq q, \quad \forall\ \xi \tag{3}$$

We perform capacity checks in Eqs (4) and (5) in terms of volume and weight, respectively, and by combining these with Eq. (6), also relate the corresponding decision variables.

$$\sum_{j=1}^{n_N}\sum_{k=1}^{n_C} v_k x_{ijk}(\xi) \leq Vz_i, \quad \forall\ i, \xi \tag{4}$$

$$\sum_{j=1}^{n_N}\sum_{k=1}^{n_C} w_k x_{ijk}(\xi) \leq Wz_i, \quad \forall\ i, \xi \tag{5}$$

$$z_i \leq \sum_{j=1}^{n_N}\sum_{k=1}^{n_C} x_{ijk}(\xi), \quad \forall\ i, \xi \tag{6}$$

To prevent possible chaotic situations in case of a disaster, the number of neighborhoods that a single neighborhood can serve and the number of neighborhoods that can serve a single neighborhood has their corresponding upper bounds α and β, expressed by Eqs. (7) and (8), respectively.

$$\sum_{j=1}^{n_N} y_{ij}(\xi) \leq \alpha, \quad \forall\ i, \xi \tag{7}$$

$$\sum_{i=1}^{n_N} y_{ij}(\xi) \leq \beta, \quad \forall\ j, \xi \tag{8}$$

Following constraint-pair given by Eqs. (9) and (10) defines the logical relationships between the corresponding variables. Note that the summation in the right-hand-side of Eq. (9) represents the total demand of all commodities in neighborhood j setting a sufficiently large number for the corresponding commodity flow.

$$\sum_{k=1}^{n_C} x_{ijk}(\xi) \leq \left(\sum_{k=1}^{n_C} d_{jk}(\xi)\right) y_{ij}(\xi), \quad \forall\ i, j, \xi \tag{9}$$

$$y_{ij}(\xi) \leq \sum_{k=1}^{n_C} x_{ijk}(\xi), \quad \forall\ i, j, \xi \tag{10}$$

Finally, constraint-pairs given by Eqs. (11) and (12) restricts the number of facilities per node and the total number of facilities, respectively, whereas the constraint given by Eq. (13) prevents allocating facilities in the neighborhoods whose safety conditions are below the required safety level. Remaining equations (Eqs. (14)–(16)) represent variable definitions.

$$z_i \leq n_i, \quad \forall\ i \tag{11}$$

$$\sum_{i=1}^{n_N} z_i \leq N_T \tag{12}$$

$$z_i = 0, \quad \exists\ i \in \{i: s_i \leq S_T\} \tag{13}$$

$$z_i \in \mathbb{Z}^+ \cup \{0\} \tag{14}$$

$$y_{ij}(\xi) \in \{0, 1\} \tag{15}$$

$$x_{ijk}(\xi),\ u_{jk}(\xi) \in \mathbb{Z}^+ \cup \{0\} \tag{16}$$

4. Case study

We illustrate our approach on a real-life case study for a district of Bursa, a metropolitan city in Turkey, with 64 neighborhoods. Considering an earthquake case study prepared by the Prime Ministry Disaster and Emergency Management Authority (AFAD) for Bursa as illustrated in Fig. 1, we create five different scenarios. Note that each of these scenarios just represents a different after-disaster situation (i.e., traffic conditions, time etc.), not a different disaster. In particular, based on our scenario construction approach, (each scenario representing a different after-disaster situation), the time it takes for the Turkish Red Crescent to reach the pre-defined shelter areas to provide relief supplies to disaster victims also differs in each scenario. As a result, the demand for each commodity is determined based on the scenarios in which an 8 h demand occurs in the best-case whereas each commodity is demanded for 72 h in the worst-case. Note that 1-day demand is the most-likely scenario. These scenarios are illustrated in Fig. 2 and summarized in Table 2 for each

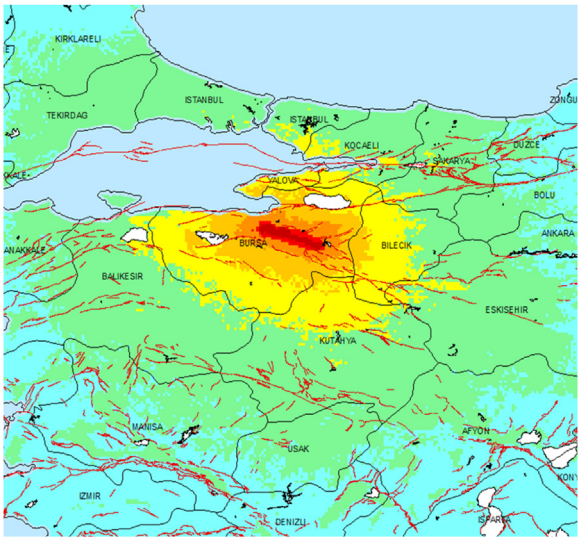


Fig. 1. Earthquake case study.

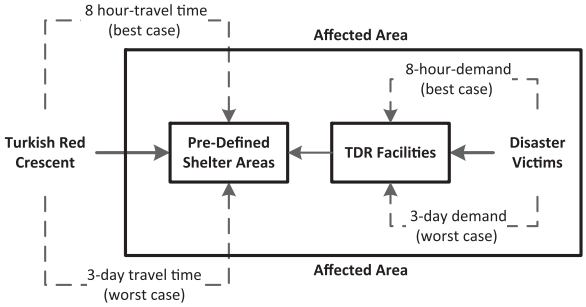


Fig. 2. Scenario construction process.

Table 2
Scenario details (commodity demands and probabilities).

Scenario	Arrival time	Water (unit-pp)	Food (unit-pp)	Medical Kit (unit-pp)	Scenario probability
S1	3 days	7.500	9.0	1.000	0.1
S2	2 days	5.000	6.0	0.667	0.2
S3	1 day	2.500	3.0	0.333	0.4
S4	16 h	1.667	2.0	0.222	0.2
S5	8 h	0.833	1.0	0.111	0.1

Table 3
Unit volumes and weights of commodities.

Commodity	Unit volume (lt)	Unit weight (kg)
Water	1.0	1.00
Food	1.0	0.25
Medical Kit	0.5	0.25

disaster victim (per person - pp). Daily requirements for a person are those of the amounts suggested by the World Health Organization (WHO) for water, and simply assumed some approximated values for food and medical kit. We further assume that the requirements are linearly dependent on time, and we thus note, for instance, that a 1-day demand is a one-third of a 3-day demand for each commodity.

We consider three different commodities as water, ready-to-eat food and a simple medical kit with their corresponding volumes and weights per unit as given in Table 3. Note that the types and amounts of the commodities are used for the illustration of the solution approach only. For a comprehensive consideration of these, the interested reader can refer to the Sphere Project.[1]

A standard TDR facility designed for such commodity storage is assumed to have a volume and weight capacity of 34,560 L and 30,480 kg, respectively. We obtain the distances between the neighborhoods using Google Maps.[2] Turkish Statistical Institute (TUIK)'s population statistics are used to determine the commodity demands.[3] Using the 2015 crime statistics provided by the district's police department, safety level for each neighborhood is simply computed as the complement of the normalized crime rate. The crime rate of a neighborhood, on the other hand, is simply defined as the ratio of the number of crimes to the total population in a particular neighborhood. As a result, after normalization, the neighborhood with the least number of crimes is assigned a safety level of one whereas the neighborhood with the most number of crimes has a safety level of zero. We assume a total number of 1000 TDR facilities available in the district and it is not allowed to allocate more than 100 TDR facilities per neighborhood. We further assume that all neighborhoods' have equal accessibility parameters (i.e., $a_i = 1, \ \forall \ i$).

We solve the deterministic model corresponding to each scenario and the stochastic programming (SP) model using the deterministic equivalent as well as the mean value problem (MVP) where the first stage decisions are made with the expectation of the most likely scenario, i.e., the third scenario with a 1-d demand. Additionally, two different safety level thresholds are considered in the solutions as 95% and 97.5%, that is, no facility is allowed in the neighborhoods whose safety levels are below the corresponding thresholds.

The results are summarized in Tables 4,5 for $\lambda = 1000$ and $\gamma = 1$.

[1] http://www.sphereproject.org/.
[2] http://maps.google.com/.
[3] http://www.tuik.gov.tr/.

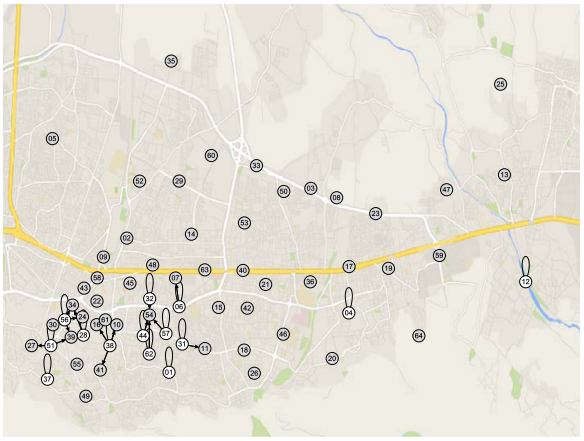


Fig. 3. Network representation of the solution.

In each scenario, both objectives (corresponding to the first and second stages) as well as the other measures of performance are presented. It is noted that when the minimum safety level is increased, meaning that it is allowed to open facilities in safer neighborhoods, the number of facilities is decreased while the quantity related to total travel-distance and unmet demand is increased accordingly, implying that the facilities serve more neighborhoods now. In the worst-case, for instance, when the minimum safety level is increased to 97.5%, the number of facilities is decreased to 103 with a travel-distance and unmet demand cost of 7,047,967. Similarly, in the best-case, the total number of facilities decreases to 17 when the minimum safety level is increased to 97.5% with the corresponding cost of 786,345.

Tables 4 and 5 also includes the results about the solutions of the stochastic program (SP) as well as the mean-value problem (MVP). According the stochastic programming model solution, 95 and 184 facilities are opened when the minimum required safety level is 97.5% and 95%, respectively, with the corresponding costs of 2,992,764 and 1,744,366 of travel-distance and unmet-demand. When the problem is transformed to a reduced stochastic program with the assumption of the most-likely scenario, 39 and 75 facilities are opened for the corresponding minimum safety levels with the respective costs of 3,263,130 and 2,293,929 of travel-distance and unmet-demand.

We finally note from the results that the expected value of the perfect information (EVPI) and the value of stochastic solution (VSS) can be computed as 53,317.2 and 214,366, respectively, when the minimum safety level is 97.5% whereas for a minimum safety level of 95%, corresponding quantities are 101,075.8 and 440,563, respectively.

We can also represent these solutions with network models where the nodes (vertices) and links (arcs) of the networks define the neighborhoods and the commodity flows between the neighborhoods, respectively. Background maps are also obtained

Table 4
Summary of results (min. safety level 97.5%).

Problem	Overall objective	First stage obj.	Second stage obj.	Average walking distance	Demand satisfaction rate	Average facility utilization
S1	7,177,967	103	7,074,967	0.1959	0.4061	0.9515
S2	4,787,362	71	4,716,362	0.1957	0.4061	0.9202
S3	2,397,473	39	2,358,473	0.1957	0.4057	0.8374
S4	1,599,270	27	1,572,270	0.1955	0.4057	0.8063
S5	803,345	17	786,345	0.1955	0.4052	0.6399
SP	3,087,764	95	2,992,764	–	–	–
MVP	3,302,130	39	3,263,130	–	–	–

SP:Stochastic program, MVP:Mean value problem.

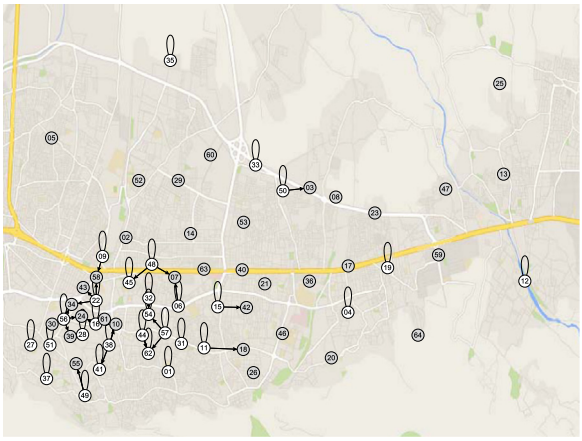


Fig. 4. Network representation of the solution (lower safety level).

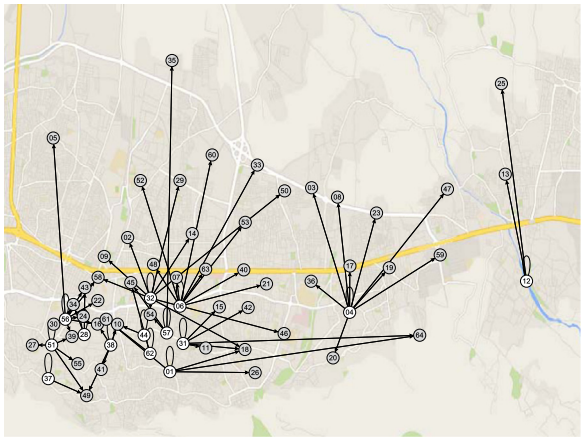


Fig. 5. Network representation of the solution (higher priority of demand satisfaction).

Table 5
Summary of results (min. safety level 95%).

Problem	Overall objective	First stage obj.	Second stage obj.	Average walking distance	Demand satisfaction rate	Average facility utilization
S1	4,309,944	200	4,109,944	0.1368	0.6598	0.9392
S2	2,877,397	137	2,740,397	0.1368	0.6404	0.9140
S3	1,446,092	75	1,371,092	0.1345	0.6382	0.8322
S4	965,772	51	914,772	0.1374	0.6399	0.8182
S5	492,252	35	457,252	0.1368	0.6393	0.5958
SP	1,928,366	184	1,744,366	–	–	–
MVP	2,368,929	75	2,293,929	–	–	–

SP:Stochastic program, MVP:Mean value problem.

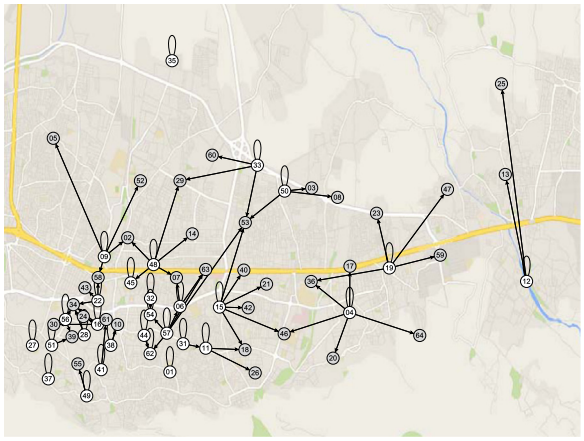


Fig. 6. Network representation of the solution (lower safety level and higher priority of demand satisfaction).

from Google Maps where the nodes are approximately represent the central locations of the neighborhoods. Although a different representation might also be used in the network model, such as modeling human flows through arcs, in our case, a directed arc from node i to node j represents the corresponding commodity flows from neighborhood i to neighborhood j. For instance, Fig. 3 corresponds to the results for the stochastic program given in Table 4 for the worst-case scenario. It is noted from the network that there are neighborhoods whose demands are not satisfied at all. We also note that the white nodes in the network represent the neighborhoods whose safety levels are above the minimum required safety level, and thus, are available for TDR facility allocation, whereas it is not allowed to open facilities due to safety conditions at the neighborhoods represented with gray nodes. By decreasing the minimum required safety level to 95%, the network shown in Fig. 4 is obtained as the solution of the corresponding stochastic program for the worst-case scenario presented in Table 5. Although it is now allowed to allocate facilities in more neighborhoods (as noted by the increased number of white nodes) to serve more neighborhoods, there are still unmet demands as seen in the network. When we increase the cost (penalty) for each unit of unmet demand, which means that the priority of satisfying demand also increases, it is noted, as expected, that the facilities serve more neighborhoods to obtain a network representation as in Fig. 5 for the minimum required safety level of 97.5%. A denser network structure is observed in this case since it is now more important to satisfy demands than to minimize the distance traveled, which is achieved simply by setting a γ value that is greater than the maximum travel distance between all neighborhood-pairs to penalize each unmet demand more than traveling the maximum distance (i.e., $\gamma = 15$). It is noted, as a result, that most of

the demands are now satisfied, though, satisfying some of which require longer travel distances. Note, for instance, neighborhood 35 is served by the facilities in neighborhood 57. An alternative allocation might be suggested by decreasing the minimum safety level to 95%. The solution corresponding to the decreased safety level is shown in Fig. 6 which represents the solution with the highest demand satisfaction rate. We now observe that neighborhood 35 is now served by the facilities allocated in the neighborhood itself. In general, it is noted that the solutions with the decreased safety levels decreases the total travel distance by compromising the safety implying the trade-off between the total distance traveled and the minimum safety level required for facility allocation. Higher definition versions of the networks are available upon request. Supplementary material are also provided for map visualizations of the corresponding solutions.

5. Conclusions

In this paper, we consider the problem of TDR facility allocation for temporary or short-term DRO, propose a solution approach and present an earthquake case study in Turkey for the illustration of our approach. A two-stage stochastic program is developed for the solution of the problem to minimize the total distance traveled, the unmet demand and the total number of facilities (considering the potential difficulties to access the facilities), where the allocation of the facilities and service decisions are performed in the first and second stages, respectively. An earthquake case study developed by the Prime Ministry Disaster and Emergency Management Authority (AFAD) is used to test our model. The case study includes five different earthquake scenarios, each represents a different after-disaster situation (i.e., traffic conditions, time etc.). As a result, the time it takes for the Turkish Red Crescent to reach the affected area differs in each scenario yielding different commodity demands. We solve each scenario as a deterministic model, as well as the corresponding stochastic program and the mean-value problem. In addition to the defined objectives of the model, quality of each solution is analyzed in terms of average walking distance, demand satisfaction rate and average facility utilization.

We note that the main contribution of our study is the development of the two-stage stochastic programming model for a special type of facility (TDR facilities) allocation problem with its own problem characteristics. In particular, differently from the others, it requires the consideration of some particular problem constraints, such as the supply-ratios, safety conditions and service levels to prevent chaotic situations and maximize the efficiency of distribution operations.

A limitation of our study is that although it considers the accessibility of the commodities in the TDR facilities during the facility allocation phase, it does not take into account the possible damages to the TDR facilities while performing the distribution operations. It might be somehow reasonable, especially in our case, to assume that the TDR facilities are functional after the disaster since the scenarios in our study are just defined to represent the different arrival times for the Turkish Red Crescent to reach the affected area in the occurrence of a single disaster. We however think including the risk of losing facilities in a more comprehensive problem setting might be considered in the future studies. Other future study directions include the extension of the stochastic model by using a probability distribution and increasing the network size to include more neighborhoods and districts. As a result of such improvements, more efficient solution approaches are expected to be necessary such as employing some decomposition approaches. We can also extend the problem domain by considering additional aspects related to real-life characteristics, such as considering commodity replenishment issues or transportation of commodities to disaster victims to minimize the distances they travel among others, each of which, we believe, if implemented correctly can significantly increase the success of DOM operations.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.ijdrr.2016.08.009.

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