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F.S. Salman, E. Yücel

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Emergency facility location under random network damage: Insights from the Istanbul case

F. S. Salman[*] and E. Yücel

College of Engineering, Koç University, Istanbul, Turkey

Abstract

Damage to infrastructure, especially to highways and roads, adversely affects accessibility to disaster areas. Predicting accessibility to demand points from the supply points by a systematic model would lead to more effective emergency facility location decisions. To this effect, we model the spatial impact of the disaster on network links by random failures with dependency such that failure of a link induces failure of nearby links that are structurally more vulnerable. For each demand point, a set of alternative paths is generated from each potential supply point so that the shortest surviving path will be used for relief transportation after the disaster. The objective is to maximize the expected demand coverage within a specified distance over all possible network realizations. To overcome the computational difficulty caused by extremely large number of possible outcomes, we propose a tabu search heuristic that evaluates candidate solutions over a sample of network scenarios. The scenario generation algorithm that represents the proposed distance and vulnerability based failure model is the main contribution of our study. The tabu search algorithm is applied to Istanbul earthquake preparedness case with a detailed analysis comparing solutions found in no link failure, independent link failure, and dependent link failure cases. The results show that incorporating dependent link failures to the model improves the covered demand percentages significantly.

Keywords: Facilities planning and design; humanitarian logistics; disaster preparedness; facility location; link failures; spatial and structural correlation

[*]Corresponding Author, F. S. Salman, ssalman@ku.edu.tr, College of Engineering, Koç University, Istanbul, Turkey

1 Introduction

Uncertainty on the timing, location and magnitude of a natural disaster, as well as how it impacts the disaster area pose serious challenges for disaster preparedness and mitigation. Among the uncertain factors, condition of lifelines carries special importance for the effectiveness of time-critical response activities. Damage to infrastructure, especially to highways and roads, adversely affects accessibility to disaster areas (Bissell, 2013). For pre-disaster logistics planning, preparedness and mitigation activities, it is important to predict the post-disaster condition of the road network at a system level. For instance, this information can be utilized in optimization models in order to generate more robust and reliable planning decisions.

We study the problem of locating emergency response facilities (ERFs, in short) as part of disaster preparedness strategies. The ERFs, where durable relief items are positioned before a disaster, serve as coordination and supply points for the distribution of relief items after a disaster. Relief item requirements throughout the disaster area are represented by demand points with estimated weights. Distribution of the items from ERFs to demand points is carried on a road network, whose node set consists of demand points, potential ERF locations and main junctions in the highway system. The links of the network represent the connections with respect to the paths in the highway system. We define our problem such that links in the network may fail during the disaster because of building collapses and/or road damages; hence, may be unavailable for the distribution of the relief items to casualty areas. For rapid disaster response, it is desired to have an ERF located sufficiently close to each demand point in the surviving network. However, this may not be possible for each demand point due to link failures. Therefore, we focus on determining the number and locations of ERFs to be used in case of a disaster so that a maximum proportion of the demand can be satisfied in reasonable time.

We formulate a stochastic integer programming model that determines the locations of ERFs among a set of potential ones with the objective of maximizing expected total demand covered within a predetermined distance parameter, over all possible network realizations. In the first stage, before a disaster occurs, facilities are located under uncertainty. In the second stage, after a disaster has occurred and a surviving network is realized, total demand covered by the open facilities is computed by a path-based approach. For this purpose, we consider a pre-determined set of alternative paths between each pair of potential facility-demand nodes so that the shortest surviving path can be used for relief item distribution.

In this setting, each link may randomly be in either operable (surviving) or non-operable (failed) status after the disaster. Hence, these links jointly form a random network whose possible outcomes are extremely large in number even when a small number of links exist. Main challenges in solving the resulting stochastic program are the vast number of outcomes (i.e., scenarios) and assessing their likelihoods. Our study differs from the stochastic emergency facility location literature in coping with these two challenges. We calculate individual link survival probabilities according to their vulnerability to a potential disaster and establish an implicit joint probability distribution while generating a sample of network scenarios randomly. In generating a scenario, we consider both spatial proximity and the vulnerability ordering among the links, and propose a new distance-based dependency model for creating correlated link failures. As a practical solution approach, we resort to a tabu search heuristic that estimates the objective function value of the candidate solutions by sample average approximation. By this way, we can explore a large sample of scenarios in short computation time.

With no doubt, it is difficult to predict which network links would fail/survive in a specific disaster situation. Nevertheless, damage risk can be assessed for road segments considering the vulnerable structures and the hazard risk of the area. However, we need to translate this link-level information to the network level by a systematic approach. It is unlikely that link failures would be independent of each other as a disaster impacts the structures within a local area in similar destructive capacity and the area possesses similar characteristics. Considering this, we propose a practical method for simulating distance-dependent correlation between link failures under an expected disaster scenario. To support our proposition, we note Tobler (1970)'s first law of geography: "Everything is related to everything else, but near things are more related than distant things". This precept leads to useful quantitative techniques for analyzing correlation relative to distance or connectivity relationships in geographic research (Miller, 2004). We adopt this concept of spatial dependence to model the functionality of an infrastructure network in a disaster-prone region and demonstrate its use in facility location decisions and how the service levels can be improved by such an approach by means of the Istanbul case study. We solved a large scale problem having around 10,000 links using our tabu search algorithm with a sample of 10,000 network scenarios generated according to the proposed distance-based link failure model. We compare the obtained solutions to those obtained by (i) no link failure, and (ii) independent link failures. We analyze various parameter settings to quantify the significance of incorporating dependent link failures in a large scale real-life problem.

The remainder of the paper is organized as follows. In Section 2, we compare our study with similar work in the literature. In Section 3, we describe the problem and the proposed solution approach. In Section 5, we provide the application of our approach to Istanbul's earthquake preparedness case. A summary of our results and possible extensions are presented in Section 7.

2 Literature review

Facility location problems for responding to large-scale emergency incidents and disasters have been studied with increasing interest in the literature. Caunhye et al. (2012) give a recent review of optimization models in emergency logistics, including a brief discussion on the contents of facility location studies. Anaya-Arenas et al. (2012) present the characteristics of location problems studied until 2012 in conjunction with network design and transportation decisions for relief distribution. Here, we review studies related to facility location in the pre-disaster stage with respect to our proposed methodology. The relevant publications can be classified as those that employ a deterministic model versus those considering uncertainty.

Deterministic models usually address problems for specific regions prone to different types of disasters. Dekle et al. (2005) study identification of disaster recovery center (DRC) locations for the state of Florida, under hurricane threat, with the aim of minimizing the total number of DRCs while covering county residents within a distance limit. In their two-stage solution process, first stage finds DRC locations by considering the distance limit and the second stage improves the solution of the first stage in terms of transportation convenience and building safety. Cheng and Tzeng (2007) propose a fuzzy multi-objective model for designing a relief delivery system for Taiwan. Görmez et al. (2010) address an emergency response facility (ERF) location problem in Istanbul metropolitan area where a destructive earthquake is expected to occur. Their objective is to minimize both the number of opened ERFs and the weighted average distance between demand points and their closest opened ERFs. They model a two-tier distribution system and consider both capacitated and uncapacitated ERFs, as well as distance limits and backup facility requirements with respect to regional vulnerability. According to their results, a small number of ERFs is sufficient to distribute relief items after a potential earthquake. In this paper, we address the case of Istanbul using a different objective and model uncertainty in road failure conditions.

In preparation for effective disaster response, Duran et al. (2011) propose a mixed-integer programming inventory location model in order to pre-position emergency items at warehouses worldwide for CARE (Cooperative for Assistance and Relief Everywhere International) organization with the objective of minimizing the response time from open warehouses to the demand points. They analyze the effect of the required number of facilities and their inventory levels on the average response time, and test the robustness of the results using simulation techniques. In a recent study, Abounacer et al. (2014) provide a multi-objective locationtransportation problem with capacity and multiple resource constraints. The objectives are to minimize the total transportation time, the number of responders needed to open and operate the facilities, and the total uncovered demand. They present an epsilon-constraint method that generates the exact Pareto front. They also provide a method that does not generate all Pareto optimal solutions but runs faster in generated test instances.

There are several studies in the literature that consider uncertainty in demand quantities, supply availability and transportation network capacity. Most of these studies employ a scenario-based approach in a stochastic programming framework, where some of them take the network condition fixed. Jia et al. (2007) propose to generalize the covering, $p-$median and $p-$center models under a set of possible emergency scenarios. Scenarios are defined by means of demand amounts and the service capability of each facility, which is reduced by the level of disruption. The aim is to minimize the regret across all emergency scenarios. Balçık and Beamon (2008) study an ERF location problem in which the relief items are classified with respect to their response time criticalities and ERFs have capacity limits for holding each item type. They present a scenario-based model that determines the number and locations of ERFs and their optimum inventory levels to maximize the satisfied demand of relief item types. The scenarios represent the uncertainties in disaster locations and demand quantities. Doyen et al. (2012) introduce a two-stage model to determine the locations of pre- and post-disaster rescue centers, the amount of relief items to be stocked and their transportation decisions under uncertain demand and transportation times. In their computational study, scenarios are generated according to earthquake intensity. They develop a Lagrangian relaxation-based heuristic approach that exhibits good performance up to 25 scenarios. Rawls and Turnquist (2010) study the problem of pre-positioning relief items and determine the locations and capacity of the storage facilities, and relief item quantities at each one. They formulate a two-stage stochastic mixed integer program that minimizes the expected costs over scenarios representing uncertainty in demand and edge capacities of the transportation network. They apply the Lagrangian $L-$shaped method to a network with 30 nodes and 58 links, and 51 scenarios representing hurricane threats. In a succeeding study, Rawls and Turnquist (2011) extend their earlier model by adding service quality constraints. In addition, a portion of the pre-positioned items may be damaged in their scenarios. According to their analysis on the same 30-node network, their newer model suggests opening more facilities with higher inventory levels compared to the former one. Noyan (2012) extends the model of Rawls and Turnquist (2010) by adding a risk measure, namely CVaR, on the total cost in the objective function. She develops decomposition algorithms to solve the extended mean-risk model and analyzes the solutions with respect to risk parameters using the data of Rawls and Turnquist (2010). Lu and Sheu (2013) propose a robust p-center model to locate relief supply facilities. They represent uncertain travel times by interval data. They minimize the worst-case deviation in maximum travel time from the optimal solution. They compare robust optimization and stochastic programming approaches in a case study to observe how conservative the solutions get as data uncertainty increases.

Unlike the scenario-based models commonly used in the humanitarian logistics literature, few studies address facility location problems on a network subject to probabilistic link failures. Early work on this subject is restricted to a single edge failure or single facility location assumption on a tree network where links fail independently. Eiselt et al. (1992) study locating a given number of facilities on a network where one of the edges fails randomly. The objective is to minimize the total expected demand disconnected from the facilities. An exact solution is found in polynomial time by solving problems with increasing number of facilities. In a succeeding work, Eiselt et al. (1996) focus on the case with an unreliable node or link. Melachrinoudis and Helander (1996) study the problem of determining the location of a single facility on a tree network with unreliable links that may fail independently. The objective is to maximize the number of nodes which are reachable through surviving paths. They propose two polynomial exact algorithms.

Hassin et al. (2009) examine the problem of locating facilities on a network with unreliable links under one or more disaster scenarios. The objective is to maximize total expected covered demand, where demand of a node is covered in a network realization if it is connected to a facility. Links fail with dependency among them according to the failure model proposed by Günneç and Salman (2011) in which a particular link e fails if any of the more reliable links fails. Since the number of possible network realizations reduces to $m + 1$, where m is the number of edges, the authors show that the problem can be solved in polynomial time by a greedy algorithm and a dynamic programming algorithm. In addition, they prove that the problem becomes NP-hard when demand coverage is defined by a distance limit. In this study, we also maximize the expected demand covered within a given distance limit but under a more realistic and generalized version of the failure model in Günneç and Salman (2011). This problem is also NP-hard.

As opposed to unreliable links, unreliable facilities have been considered, especially in the context of supply disruptions (e.g., those in Snyder and Daskin (2007),O'Hanley et al. (2013)). Jeong et al. (2014) study a capacitated multi-level facility location problem where the facilities may shutdown due to damage and the stocked relief items will not be available with given probabilities after a disruption. In their case studies they assume that only one facility may be damaged to reduce the number of scenarios. Liberatore et al. (2012) model disruptions of facilities with correlation effects between them in a three-level facility protection problem with an attacker, a defender and customers. They define a correlation matrix that represents the extent to which other facilities are affected when a target facility is disrupted. In their numerical study, the correlation coefficients are defined with respect to distances between facilities. However, probabilistic disruptions are not considered. Sunil et al. (2013) analyze random facility disruptions where facilities can be protected with additional investments. Assuming that all facilities fail with the same probability, they investigate the impact of inaccurate estimation of the disruption probability both under independent and correlated disruptions. In contrast, our proposed dependency structure for link failures does not require assessing correlation coefficients between all pairs of edges, which is quite challenging in a large-scale problem.

Li et al. (2013) acknowledge the difficulty in modeling interdependent facility failures in an efficient and compact form. For this purpose they suggest a specific kind of dependency generation method which would give more optimistic scenarios compared to our dependency model. They propose to define supporting facilities in addition to the facilities to be established. The failure of a facility is conditioned to the failure of all of its k supporting facilities so that common supporting facilities generate correlation. It is assumed that each supporting facility fails independently with an identical disruption probability p. They select both the supporting and main facilities by a mixed integer programming model.

Our study differs from existing ones in terms of how we model network reliability and generate network scenarios respectively. Joint link failures occur according to proximity and reliability ordering of the links. We show that accounting for this kind of dependency in the facility location problem provides substantial advantage in expected demand coverage compared to assuming independent failures with a case study of Istanbul.

3 Problem description and the optimization model

We consider an undirected graph $G = (V, E)$, with node set $V = \{1, 2, \ldots, n\}$ and edge set $E = \{(i, j) \mid i, j \in V\}$. J denotes the set of candidate ERF locations, I denotes the set of demand points, and K denotes the set of edge junction points, where $J \cup I \cup K = V$. Each demand point $i \in I$ has a demand amount d_i. This input parameter is estimated by considering the population affected from the disaster in the represented area according to its seismic and structural risk. In essence, it serves as the weight of the demand point in the objective so that more risky and populated areas have priority. The potential facility locations can be selected to be close to critical supply locations such as airports, ports, etc. A subset of the edge set, $L \subseteq E$, consists of links representing paths in the road network that are subject to damage risk. For each link $(i, j) \in L$, a random variable ξ_{ij} represents the post-disaster status of the link. Link (i, j) is said to be functional (surviving) if ξ_{ij} attains a value of 1; and 0, otherwise. For each link (i, j), a survival probability p_{ij} is given or generated by the method described below. The surviving network is defined by the vector ξ and the reliable edges, $E - L$.

In this setting, uncertainty can be modeled through the use of a set S of discrete scenarios indexed by $s \in S$, each with a probability of occurrence, $P(s)$, where $\sum_{s \in S} P(s) = 1$. In a scenario s, the links that survive are defined by parameters a_{ij}^s. That is, $a_{ij}^s = 1$, if link (i, j) survives in s; and $a_{ij}^s = 0$, otherwise. The number of all possible scenarios is 2^m, where m is the number of unreliable links (i.e., $m = |L|$).

From each $j \in J$ to each $i \in I$, a set of k alternative paths in G, Π_{ji} , is given. A path $\pi_{jip} \in \Pi_{ji}$ has length l_{jip} and includes a sequence of nodes $i_1\, i_2 \cdots i_u$, where $i_1 = j$ and $i_u = i$. In order for path π_{jip} to survive in a scenario s, any link $(i_q, i_{(q+1)})$ in the path should survive, i.e., $a^s_{i_q,i_{(q+1)}} = 1, \forall q = 1, 2, \ldots, u-1$. A demand point i is covered by facility location j in scenario s if and only if there exists at least one path among the surviving paths in Π_{ji} that has length less than or equal to a predefined coverage distance limit R. The 0-1 parameter c^s_{ij} indicates if the demand point i is covered by a facility at location j in scenario s. Appendix A lists the notation used throughout the paper.

The problem is to choose at most Q ERF locations from the set J. The facility location decisions are made in the pre-disaster stage, before any scenario is realized. After a disaster occurs, a specific scenario is realized and relief items should be distributed from the open ERFs through the surviving transportation network. Demand will be supplied from the stocks, local and international vendors, and in-kind donations that arrive in time. Hence, we do not consider capacity decisions and assume that a demand point can be covered by any of the accessible ERFs within the specified distance limit. The amount of relief items such as relief aid kits, blankets, heaters, medicine, etc., to be prepositioned at the facilities should be decided after the facility location decisions are given, as tactical level decisions. In the tactical level inventory control problem other considerations such as perishability, funding limitations, etc., can be considered as well.

The facility location problem can be formulated as a deterministic 0-1 linear program, say (M), in which the objective is to maximize the expected covered demand, C, over all scenarios, S. Maximum coverage models are used frequently for emergency facility location when the resources are not enough to cover all demand locations. These models are also used for the deployment of ambulances, where availability of these resources are of concern. Li et al. (2011) review covering models for emergency response location and solution approaches for them.

Decision Variables

x^s_{ij}	equals 1, if demand point i is covered by a facility at location j in scenario s; and 0, otherwise.
y_j	equals 1, if a facility is located at node j; and 0, otherwise.
z^s_i	equals 1, if demand point i is covered in scenario s; and 0, otherwise.

Parameters

$P(s)$	occurrence probability of scenario s.
d_i	amount of demand at node i.

Q	maximum number of facilities to be opened.
c_{ij}^s	equals 1, if demand point i is covered by a facility at location j in scenario s; and 0, otherwise.

$$(M): \text{Maximize} \quad C = \sum_{i \in I} \sum_{s \in S} P(s) d_i z_i^s \tag{1}$$

subject to

$$x_{ij}^s \leq c_{ij}^s y_j, \qquad \forall i \in I, j \in J, s \in S, \tag{2}$$

$$\sum_{j \in J} y_j \leq Q, \tag{3}$$

$$z_i^s \leq \sum_{j \in J} x_{ij}^s, \qquad \forall i \in I, s \in S, \tag{4}$$

$$x_{ij}^s, y_j, z_i^s \in \{0, 1\}, \qquad \forall i \in I, j \in J, s \in S. \tag{5}$$

Constraint (2) ensures that a demand point i is covered by facility j in scenario s if and only if there exists a surviving path shorter than the coverage distance limit R between i and j in s. Constraint (3) guarantees that at most Q number of ERFs are opened. Constraint (4) enforces that a demand point i is covered by an open facility in scenario s only if at least one facility is reachable within the distance limit. Finally, Constraint (5) defines the binary variables in the model.

The c_{ij}^s parameters can be calculated by solving an all-pairs shortest path problem for each scenario in pre-processing stage. The number of binary variables and constraints is in the order of $|I|\,|J|\,|S|$. For relatively small problem instances with a small number of scenarios, (M) can be solved with a general-purpose IP solver in reasonable time. However, as the size of the problem instance increases (larger number of locations, demand points, and scenarios), memory becomes a limiting factor and as a result, IP solvers cannot find a good solution within a reasonable computation time. According to our experiments on a realistic large-scale network with nearly 250 nodes and 10,000 links, a workstation with Xenon E5220 @ 2.27 Ghz processor and 48 GB of memory could not afford to solve the model for 700 scenarios.

4 Solution method

Exact calculation of network reliability measures over the entire possible scenarios is NP-hard (Konak and Smith, 2006). For a problem instance with m unreliable links, the evaluation of a solution requires the calculation of the demand coverage in 2^m possible scenarios. As network size gets larger (even when 50 links exist) this calculation requires extremely high computation time and memory allocation. One practical approach to alleviate the computational difficulty is to solve the stochastic program over a sample of scenarios. Larger samples provide better estimation accuracy, while making the solution of the sample average approximation problem computationally challenging. To reduce computation time and memory allocation, we utilize a tabu search algorithm for the ERF location problem. We take advantage of a sampling average approximation algorithm that generates scenarios by determining link failures either independently or with a distance-based dependency. The generated sample scenarios are used to estimate the expected covered demand by a candidate solution.

4.1 Scenario generation

Although there exists 2^m possible scenarios for a problem instance with m unreliable links, most of the possible scenarios are expected to be very improbable in a disaster situation. We generate a sample of N scenarios, by proposing a dependent link failure scheme that aims to capture both spatial correlation in the disaster area by means of proximity, and the vulnerability level of the roads by considering the intensity of the disaster throughout the affected area. In this way, the goal is to eliminate the extensive number of unrealistic scenarios and generate scenarios that represent the most likely situation.

While generating a scenario s, a link $(i, j) \in L$ may fail due to a possible disaster independently or with statistical dependence. We call these two possibilities as independent failure case (IF) and dependent failure case (DF), respectively, and generate N network realizations that constitute the set S for each case. The generated scenarios are considered to be equally-likely, i.e., $P(s) = 1/N$ for all $s \in S$. Although it is unrealistic that all links will be operational after a major disaster, we also analyze the *no link failure* case for benchmarking. In this deterministic problem, there exists only one scenario s in S with $P(s) = 1$ and $a^s_{ij} = 1$ for all $(i, j) \in L$.

Independent failure case (IF)

We generate each scenario s by independent Bernoulli trials for each link $(i, j) \in L$ with its survival probability, i.e., p_{ij}. Each time, we generate a new random number r between 0 and 1. We set $a^s_{ij} = 0$, if p_{ij} is less than r, meaning that the corresponding link (i, j) fails in scenario s; otherwise, we set $a^s_{ij} = 1$, meaning that it survives in s.

Dependent Failure Case (DF)

We model failure dependency among links in line with the *Vulnerability-Based Dependency* (VB-dependency) model of Günneç and Salman (2011). In VB-dependency model, the set of links, L, is partitioned into a set of disjoint subsets, called as VB-dependent subsets, where the links in a VB-dependent subset do not have to be necessarily geographically adjacent to each other. A link in a VB-dependent subset fails if any of the stronger links in the same subset fails. Our model differs from the VB-dependency model of Günneç and Salman (2011) as follows. For a given dependency distance limit $W \geq 0$, we construct a dependency set, N_{ij}, for each link $(i,j) \in L$ that denotes the set of neighbor links of the link (i,j) that reside within W distance units from (i,j). Since our dependency model is based on the predefined dependency distance limit W, we call it *Distance-Based Dependency* model. We measure the distance between two links as the *minimum* distance between the corresponding four pairs of nodes. The distance between two links can be defined according to different metrics and proximity measures.

Definition 1. (*Distance-Based Dependency*) Given a network with link set L subject to failure due to a disaster event, the network is said to have *Distance-Based Dependency* (DB-dependency) under a disaster scenario, if:

- for each link $(i,j) \in L$, there exists a dependency set $N_{ij} \subset L$ that is composed of the links in L that are within W distance limit from (i,j), and
- the failure of a link $(i,j) \in L$ with survival probability p_{ij} implies the failure of every link $(i',j') \in N_{ij}$ that has smaller survival probability compared to (i,j), i.e., $p_{i'j'} < p_{ij}$.

It is important to note that according to the DB-dependency model, a link (i,j) may appear in more than one dependency set; hence, its failure may be caused by any one of the dependency sets that it belongs to, in contrast to the set-based link failure scheme of Günneç and Salman (2011). The method can accommodate influence factors specific to the disaster type by defining the dependency sets accordingly.

In order to generate a scenario s with respect to DB-dependency, for each link $(i,j) \in L$, we take a random number, r, between 0 and 1. We set $a^s_{ij} = 0$ and $a^s_{i'j'} = 0$ for all $(i',j') \in N_{ij}$ with $p_{i'j'} < p_{ij}$, if the survival probability of (i,j), p_{ij}, is less than r, meaning that link (i,j) and its weaker neighboring links fail in scenario s. Otherwise, we set $a^s_{ij} = 1$, meaning that it survives in s.

4.2 Tabu search algorithm

We propose a tabu search algorithm that searches the neighborhood of a current solution defined by the open/close status of the potential ERF locations. Tabu search has been applied to facility location problems such as p-median (Rolland et al., 1997; Resende and Werneck, 2007), uncapacitated facility location (AlSultan and AlFawzan, 1999; Ghosh, 2003; Sun, 2006), and maximum coverage location (Gendreau, 1997) with success. The readers can find detailed information on the tabu search framework and its applications to several problems in Glover and Laguna (1993), Glover and Laguna (1997) and Hertz and De Werra (1991).

In our algorithm we represent the selected facility locations by a binary vector. A feasible solution is modified to obtain feasible neighboring solutions by keeping the number of open facilities at Q. Formally, a binary vector y, (where $y[j] = 1$, if ERF j is opened; and $y[j] = 0$, otherwise) is feasible if it has Q 1's. Starting with a random solution, at each iteration the algorithm moves from the current solution to the best neighboring solution until a predetermined number of iterations, η, is reached. We use the swap (pairwise exchange) move, in which an open facility is closed and a closed potential facility is opened, to generate $Q(|J|-Q)$ neighboring solutions from the current solution. Swapping facilities is a standard move in facility location problems. To prevent the repetition of the same solutions, a tabu list keeps the swap move which gives the best neighboring solution for the next θ iterations, where θ represents the tabu tenure. The best move that is not in the tabu list is taken as the next solution. However, if a tabu neighboring solution is the best solution found so far, the algorithm allows selecting it as the solution of the next iteration. This is called the aspiration criterion. For diversification purposes, in 10% of the iterations, the algorithm allows to select a neighboring solution that does not improve the current best solution as the next solution. We provide the pseudo-code of the tabu search algorithm in Algorithm 1.

Algorithm 1 Tabu search algorithm

Input: R, $\Pi_{ji}, \forall j \in J, i \in I$, d_i

1: Generate each sample scenario s of the scenario set S and their probabilities, $P(s)$'s, using the average sampling method.
2: Randomly generate an initial solution y of a binary vector of size $|J|$.
3: Calculate the objective value, i.e., the expected coverage value of y, $C(y)$.
4: $y^* = y,\ C(y^*) = C(y)$
5: Initialize *Tabu List*.
6: **while** termination criteria not satisfied **do**
7:     **for** each neighboring solution, y', of y **do**
8:         Calculate $C(y')$.
9:         Keep the neighboring solution y', which provides the largest expected coverage value.
10:     **end for**
11:     **if** y' is not in the *Tabu List* or y' is the best solution ever **then**
12:         $y = y^* = y',\ C(y) = C(y^*) = C(y')$.
13:         Add the current move to the tabu list T.
14:     **else**
15:         Generate a random number, r, between 0 and 1.
16:         **if** $r \leq 0.1$ **then**
17:             $y = y',\ C(y) = C(y')$.
18:             Add the current move to the tabu list T.
19:         **else**
20:             Set y' as the next best neighboring solution and go to Line 11.
21:         **end if**
22:     **end if**
23: **end while**

For DF and IF cases, sample average approximation is used to estimate the objective function value, $C(y)$, for a neighboring solution y (see Algorithm 1). The estimated value is calculated as the average covered demand over the N scenarios generated by the sampling algorithm. Recall that for a solution y, the demand of a point $i \in I$ is covered in scenario $s \in S$, if there exists an open ERF at location j (i.e., $y[j] = 1$) with at least one path among the alternative paths in Π_{ji} that survive in s having a length less than or equal to the predefined coverage distance limit R. As stated in Section 3, a path $\pi_{jip} \in \Pi_{ji}$, which follows a sequence of nodes $i_1\, i_2 \cdots i_u$, survives in a scenario s, if all links in the path survives, i.e., $a^s_{i_q,i_{(q+1)}} = 1$, $\forall q = 1, 2, \ldots, u-1$. Thus, the algorithm checks the survival of the relevant paths.

Algorithm 1 Evaluating the expected coverage value, $C(y)$, of a solution y in the tabu search algorithm

1: $C(y) \leftarrow 0$
2: **for** each $s \in S$ **do**
3:     **for** each $i \in I$ **do**
4:         $z_i^s \leftarrow 0$
5:         **for** each $j \in J$ such that $y[j] = 1$ **do**
6:             **for** each $\pi_{jip} \in \Pi_{ji}$ that follows the sequence of nodes $i_1\, i_2 \cdots i_u$ **do**
7:                 **if** $l_{jip} \leq R$ **then**
8:                     $z_i^s \leftarrow 1$
9:                     **for** $q = 1, 2, \ldots, u-1$ **do**
10:                         **if** $a^s_{i_q, i_{(q+1)}} = 0$ **then**
11:                             $z_i^s \leftarrow 0$
12:                         **end if**
13:                     **end for**
14:                     **if** $z_i^s = 1$ **then**
15:                         go to Line 20
16:                     **end if**
17:                 **end if**
18:             **end for**
19:         **end for**
20:         $C(y) \leftarrow C(y) + d_i z_i^s P(s)$
21:     **end for**
22: **end for**

We remind that, for the NF case, there is only one scenario $s \in S$ (that is, $N = 1$ and $P(s) = 1$), in which all links survive.

5 Application to Istanbul's earthquake preparedness

We applied our solution method provided in Section 4 to guide the strategic decisions on selecting supply points for emergency relief in Istanbul. The active fault zone in the Marmara Sea that lies about 20 km south of the city poses an extremely high seismic hazard risk (Pichon et al., 2001). Earthquake probability calculations for the Marmara Sea in Parsons (2004) show that the probability of a 7 or larger magnitude earthquake is 38%, and incorporation of stress transfer raises it to 53 with 18% error margin. In addition, the rapid and unplanned growth of the city within the last 30 years increases the vulnerability. Experiencing the devastating consequences of the 1999 earthquake that was epicentered 110 km east of Istanbul underlined the need for earthquake preparedness and response planning. The 7.6 M earthquake resulted in over 20,000 fatalities, nearly 50,000 injured, about

500,000 homeless and estimated 3 to 6.5 billion U.S. dollars damage in Istanbul, Kocaeli and Sakarya Provinces. In 2000, Istanbul Metropolitan Municipality (IMM) established a Disaster Coordination Center (AKOM). Detailed earthquake risk assessment studies were conducted (JICA, 2002; Erdik et al., 2003) and an earthquake master plan was developed in collaboration with four universities. The findings of these studies and subsequent developments have been summarized by Erdik and Durukal (2008). Estimations from a credible worst-case earthquake scenario show that a total of approximately 500,000 households could be in need of shelter.

To increase the response capability, AKOM plans to establish facilities to pre-position relief items. These facilities (ERF) are planned to act as supply and coordination points from where relief items will be distributed to local distribution points in the affected area. AKOM has determined a number of potential ERF locations with respect to transportation effectiveness and resistance to a possible earthquake. While one such facility has already been established, the locations of others still remain to be decided. This problem has been described in an earlier study by (Görmez et al., 2010), who provided detailed analyses and guidelines by deterministic bicriteria models. However, the facility location models in (Görmez et al., 2010) did not consider the road damage risk.

Next, we explain how we generated the data and provide a detailed analysis of the best solutions found for the dependent, independent, and no link failure cases.

5.1 Data generation

The most important data for our model are demand and link reliabilities. We propose to determine them according to hazard risk of the area under consideration with respect to a particular type of disaster. For instance, FEMA's Hazus risk assessment software program (http://www.fema.gov/hazus) provides estimates of losses from floods, hurricane winds and earthquakes. Hazus uses Geographic Information Systems (GIS) technology to illustrate physical, economic and social impacts of disasters. Such a hazard risk analysis tool can be used to determine link reliability and demand values. We suggest generating the reliability of each link as a function of (1) a predetermined score representing the structural vulnerability of its components, (2) its distance from the epicenter of the expected disaster scenario, and (3) the measure of disaster intensity. Demand of a node can be taken as its population times a risk factor specific to the area it represents. Link distances can be obtained from a GIS by finding shortest paths.

In our illustrative case, demand and link reliabilities are based on the risk of the building stock, road components and segments according to an existing risk analysis study for Istanbul. In 2000, IMM collaborated with the Japan International Cooperation Agency (JICA) on the identification of potential disaster scenarios in Istanbul and their impact on the city. The resulting JICA report (JICA, 2002) provides four highly probable earthquake scenarios in the Marmara fault zone, with specified magnitude, rupture locations and lengths. Detailed analyses are conducted for two of these scenarios, namely, Model A which is suggested to be the most probable scenario, and Model C, to be the worst-case scenario with magnitudes 7.5 and 7.7, respectively. Based on building damage estimates, the number of people in need of shelter and those expected to be injured are given for each district for Model A and Model C scenarios. In this study, we used the casualty percentages of each district in Istanbul provided in (JICA, 2002) to generate demand amounts according to the most recent population data at the neighborhood level. Link survival probabilities are based on the risk maps and classification of risky highway components. We conducted analysis with both of the two scenarios, Model A and Model C, and observed that the results are very similar. Therefore, we present the results for the instance that uses the data for Model C (which is also taken as the main scenario in (JICA, 2002)).

5.1.1 Network nodes

Network nodes consist of potential ERF locations, demand points and road junction points.

ERF locations: There are 41 potential facility locations that have been specified by AKOM. Figure 1 shows the potential ERF locations on the Istanbul map.

Demand Points: We obtained the Istanbul population data at the neighborhood level from the Turkish Statistical Institute. We clustered the 964 neighborhoods in our study area visually on the map according to their population density and obtained 186 demand point locations. We defined each district center as a demand point. Moreover, we included additional demand points in densely populated areas within each district such that clusters with a population of more than 10,000 have representative points. Figure 2 illustrates the identified demand point locations in Istanbul that are colored with respect to population values.

Relief material requirements, i.e. the demand value at each demand point is set to the estimated refugee population in the corresponding cluster, assuming the commodities needed

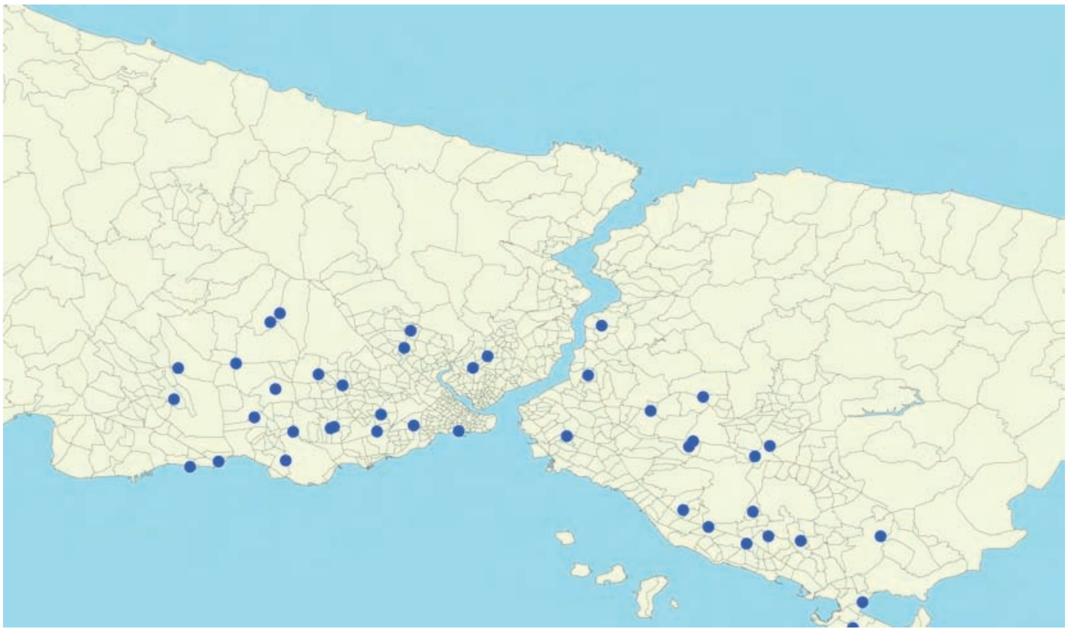


Figure 1: Potential ERF locations and the neighborhoods

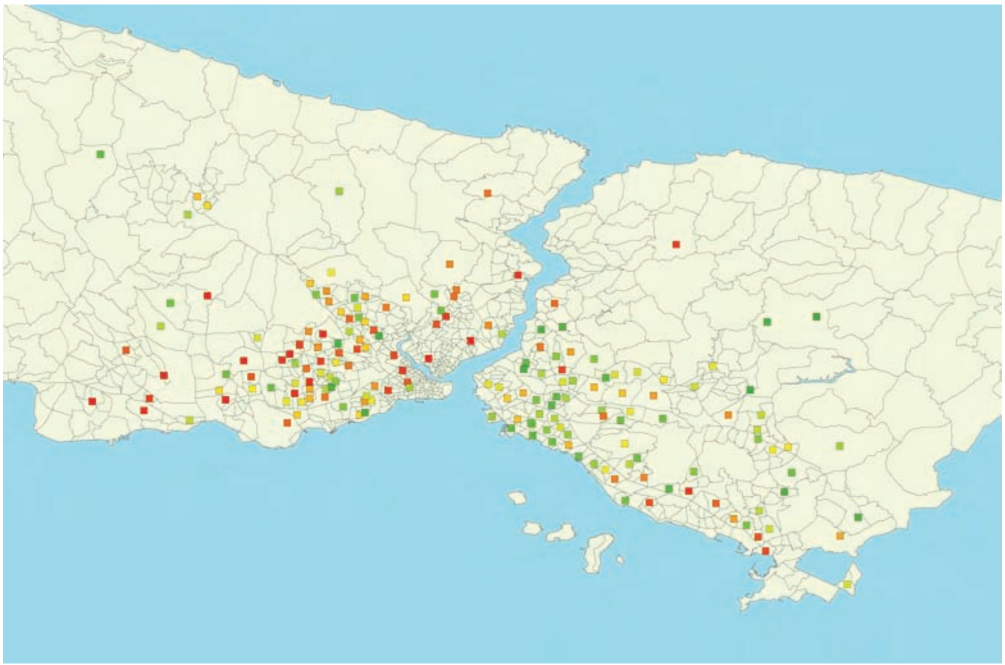


Figure 2: Identified demand points in Istanbul (Green: low, Red: high population; the reader is referred to the web version of this article)

by each refugee are identical. In the JICA report, refugee population is estimated by taking respectively, 100%, 50% and 10% of the surviving population in heavily, moderately and partially damaged buildings. The total estimated demand amount for Model C is $197,342$, indicating that around 200,000 people would be in need of aid. Figure 3 shows the demand distribution geographically.

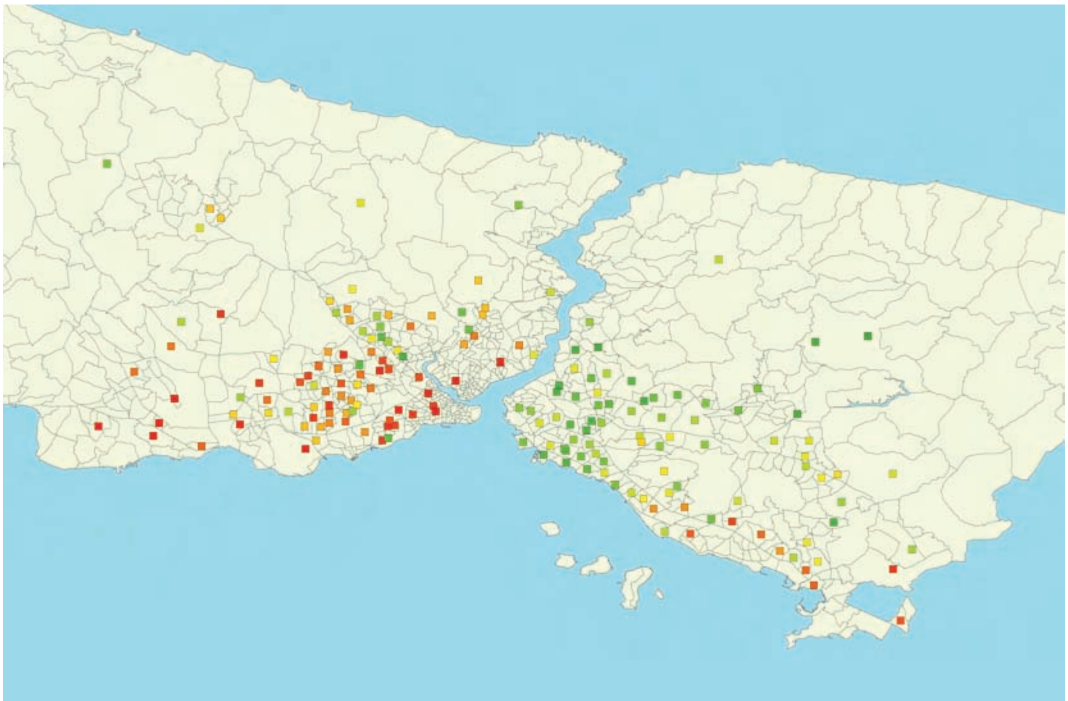


Figure 3: Demand distribution throughout the city (Green: low demand, Red: high demand)

Junction Points: In the context of traffic networks, a junction is an intersection point where several or different types of routes meet or link. In our study, we identify the entries and exits of bridges and viaducts in the highways (Figure 4) as separate nodes in the network because of their critical role and their vulnerability to a possible disaster. By this way, we can consider the road sections that have end points at these junction points as separate transportation links in the network that may fail due to a disaster.

5.1.2 Network Links and Paths

The transportation link set L is composed of road segments among potential ERF locations, demand points and major road junction points in the network. We generated the actual road distances of these links by taking the shortest path lengths in the street map of Istanbul, using ArcGIS package (see Figure 5 for the network). Then, in the resulting network, we generated 10 alternative paths as the 10 shortest paths between each potential ERF location $j \in J$ and demand point $i \in I$ pair, that constitute the set Π_{ji}. We calculated

Figure 4: 40 road junction points in Istanbul

the distance, l_{jip}, for each path π_{jip} in Π_{ji}.

Table 1 summarizes the size of network components.

Table 1: Istanbul Network Components

Number of nodes in the network	267
Number of clustered demand points	186
Number of potential facility locations	41
Number of road junction points	40
Number of edges in the network	9,587
Number of paths generated	76,260

5.1.3 Probability Generation

In our case, the p_{ij} for each link $(i, j) \in L$ is determined according to three criteria: (1) the seismic zone factor based on where (i, j) is located (referred to as β_{ij}), (2) its distance from the fault line of the earthquake (referred to as r_{ij}), and (3) the magnitude of the

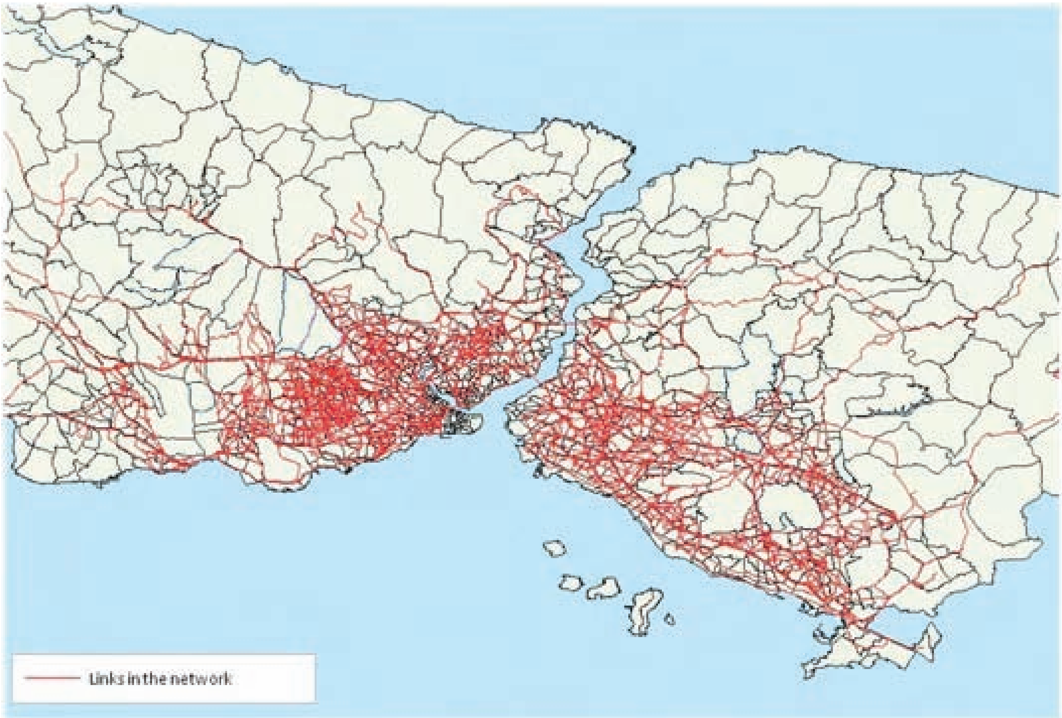


Figure 5: Links representing road segments

earthquake, μ. We calculate p_{ij} as

$$p_{ij} = 1 - \beta_{ij}\text{PGA}_{ij},$$

where PGA_{ij} is the *peak ground acceleration* at link (i, j). It is formulated in Panoussis (1974) as

$$\text{PGA}_{ij} = \alpha \frac{e^{0.8\mu}}{(r_{ij} + 40)^2},$$

where α is a parameter that is used to predetermine the range of survival probabilities.

In the JICA report, Istanbul is partitioned into four zones according to the seismic intensity of the expected earthquake (see Figure 1(b) for Model C in Appendix B). Seismic zone factors $f_1 = 0.95$, $f_2 = 0.85$, $f_3 = 0.75$, and $f_4 = 0.65$ represent the damage risk of the region in an earthquake (zone 1 is the most risky region). We set β_{ij} to one of $\{f_1, f_2, f_3, f_4\}$, depending on the position of the link. In Model C, it is estimated that $\mu = 7.4$. Based on our consultation with experts from the Highway Administration and the information in the JICA report, we decided that survival probabilities should be distributed between 0.70 and

0.90 for Model C. Accordingly, we set $\alpha = 2$.

6 Computational analysis

We first compare the solutions found by the proposed tabu search algorithm and the 0-1 programming formulation (M) given in Section 3 on a small sample to validate the performance of the tabu search algorithm. Next, we solve the ERF location problem with the tabu search algorithm using 10,000 scenarios. We analyze the effects of problem parameters (number of scenarios, number of ERFs to open, coverage distance limit, and dependency distance limit) and the assumptions about the characteristics of link failures (dependent, independent, or no failure cases) on the quality of the solutions generated. Decision makers may conduct a similar study with different parameter choices based on other criteria, such as budget limitations or service level goals.

The computational experiments were performed on a workstation with Xeon E5520 @ 2.27 GHz processor and 48GB of memory. GAMS 23.3 was used to create the IP models and CPLEX 12.2 was employed to solve them to optimality.

Our algorithm involves two parameters: maximum number of iterations allowed, η, and the tabu tenure, θ. On the basis of preliminary tests, we set these parameter values as $\eta = 20$ and $\theta = 5$.

6.1 Evaluation of the solution quality of the tabu search algorithm

In order to investigate the performance of the proposed tabu search algorithm, we solve the IP formulation developed in Section 3 on Istanbul's network with small sized samples. We took five different samples and conducted five runs. For each run, we generate N distinct scenarios according to the DF case and run our heuristic approach and with the generated scenarios for $Q = 8$, $R = 10$ km, and $W = 15$ km. The IP formulation is solved by setting the relative gap tolerance option, *optcr*, to 0.0001. The number of scenarios, N is set to 700 since the IP formulation causes an out of memory situation for larger scenario sizes in the computation platform specified above. We present the results in Table 2. In the table, for each run and the two solution approaches, column t(m) reports the elapsed CPU minutes to get the solution, column C provides the expected demand coverage of the solution, and column $\%C$ lists the percentage of C in the total demand.

According to the results, the TS approach generates the optimal solutions in all cases in considerably shorter time compared to the IP formulation. We conclude that the TS

Table 2: Comparison of the performances of TS approach and IP formulation with $N = 700$ for Istanbul's network with Model C

	TS approach				IP formulation			
Run	t(m)	Solution (open ERFs)	C	$\%C$	t(m)	Solution (open ERFs)	C	$\%C$
1	2	9,12,20,23,27,28,30,33	111,395	56	11	9,12,20,23,27,28,30,33	111,395	56
2	2	9,12,21,23,27,28,30,33	111,981	57	11	9,12,21,23,27,28,30,33	111,981	57
3	2	9,12,20,23,27,28,30,33	111,724	57	20	9,12,21,23,27,28,30,33	111,724	57
4	2	9,12,21,23,27,28,30,33	111,420	56	27	9,12,15,20,23,27,28,33	111,420	56
5	2	9,12,20,23,27,28,30,33	111,482	56	12	9,12,21,23,27,28,30,33	111,482	56

approach is capable of providing high quality solutions. Furthermore, the TS algorithm works with a much larger number of scenarios in a reasonably short period of time, as seen in the next section.

6.2 Sample size analysis

As stated in Section 4, in case of unreliable networks (for DF and IF cases), the evaluation of the objective function over all possible scenarios gets impossible as the number of links increases. In order to solve large-scale problems, our heuristic approach generates N scenarios for both of DF and IF cases and estimates the objective function value of a solution as the average covered demand over the generated scenarios. From this point on, we use the term *DF scenarios* for the scenarios generated for the DF case, and the term *IF scenarios* for the scenarios generated for the IF case.

In order to analyze the effect of the number of scenarios, N, on the solution quality, we conducted experiments for varying N ($N = \{2,000, 4,000, \ldots, 20,000\}$) with $Q = 8$, $R = 15$ km, and $W = 15$ km. The fixed parameters are set according to the results of our analysis provided in the following subsections. The NF case gives a deterministic upper bound on the total coverage. We generated 10 runs for each setting and each failure case. Among these 10 runs, the results with the best expected demand coverage for DF and IF cases and the best demand coverage for the NF case are provided in Table 3. In the table, for each N value, we report the following results. For each failure case, column C reports the expected demand coverage of the best solution found by the tabu search *evaluated with the DF scenarios*, column $\%C$ provides the percentage of C in the total demand, and column t(m) gives the elapsed CPU minutes to get the solution. For the IF case, column C_{IF} provides the expected demand coverage of the best solution found by the tabu search *evaluated with* *the IF scenarios.* Column C_{NF} gives the demand coverage of the best solution found by the tabu search algorithm in the deterministic no failure case. Column F provides the number of failed transportation links averaged over the scenarios generated for DF and IF cases.

Table 3: Sample size analysis for Istanbul's network for Model C

	DF				IF				
N	t(m)	C	$\%C$	F	t(m)	C_{IF}	C	$\%C$	F
2,000	15.9	157,400	80	3,544	14.8	174,242	143,486	73	1,850
4,000	30.5	157,365	80	3,538	28.6	174,272	141,931	72	1,851
6,000	63.6	157,292	80	3,537	61.5	174,252	142,319	72	1,851
8,000	61.9	157,423	80	3,540	58	174,494	143,827	73	1,851
10,000	76.7	157,517	80	3,537	71	174,590	141,949	72	1,851
12,000	90.4	157,582	80	3,538	83.6	174,652	142,801	72	1,851
14,000	104.9	157,603	80	3,540	97.4	174,648	144,628	73	1,851
16,000	123.2	157,492	80	3,540	115	174,579	143,346	73	1,851
18,000	189.2	157,487	80	3,538	173.5	174,537	141,978	72	1,851
20,000	211.2	157,464	80	3,538	194.9	174,519	142,708	72	1,851

	t(min)	C_{NF}	C	$\%C$
NF	0.05	178,644	120,160	61

Total Number of Links: 9,578	Total Demand: 197,342

According to the results presented in Table 3, for both DF and IF cases, there is no significant change on the percentage of demand covered as N varies. However, run time increases significantly as N gets larger than 10,000 in both DF and IF cases. Hence, we set $N = 10,000$ in the remaining analysis.

In Table 4, we provide the results of each of the 10 runs with $N = 10,000$ for DF and IF cases. The number of common ERFs found in the solutions of each run is 5 for the DF case and 4 for the IF case. Ten runs generate 3 different solutions for the DF case and 8 different solutions for the IF case. Additionally, 7 of the runs found the same solution for the DF case. We conclude that having 10 runs for the tabu search and generating $10,000$ scenarios for each run is sufficient for the DF case.

We provide the run time of the proposed algorithm and the required time for each part of the algorithm (i.e., scenario generation and tabu search) for varying N in Figure 6, for the DF case. While the time required for scenario generation is negligible compared to the time required for tabu search, as N increases, time required for tabu search increases as seen in the figure.

Table 4: The results of each run for DF and IF cases with $N = 10,000$

	DF			IF			
Run	Solution (open ERFs)	C	$\%C$	Solution (open ERFs)	C_{IF}	C	$\%C$
1	15,20,22,24,25,27,28,29	157,481	80	9,12,15,19,24,25,32,38	174,506	144,028	73
2	5,20,24,25,27,28,29,32	156,514	79	6,9,12,15,18,24,32,38	174,583	142,697	72
3	15,20,22,24,25,27,28,29	157,388	80	6,9,12,15,19,24,32,38	174,590	141,949	72
4	15,20,22,24,25,27,28,29	157,363	80	7,9,12,15,18,24,25,32	174,490	143,702	73
5	15,20,22,24,25,27,28,29	157,458	80	6,7,9,12,15,18,24,32	174,495	141,809	72
6	15,20,22,24,25,27,28,29	157,466	80	6,9,12,15,18,24,32,38	174,544	142,664	72
7	8,15,20,22,24,25,27,29	157,517	80	9,12,15,18,23,24,32,38	174,528	136,202	69
8	15,20,22,24,25,27,28,29	157,368	80	6,7,9,12,15,19,24,32	174,554	141,259	72
9	5,20,24,25,27,28,29,32	156,564	79	6,9,12,15,18,24,32,38	174,555	142,525	72
10	15,20,22,24,25,27,28,29	157,452	80	6,9,14,15,18,24,32,38	174,514	140,767	71
Best	8,15,20,22,24,25,27,29	157,517	80	6,9,12,15,19,24,32,38	174,590	141,949	72

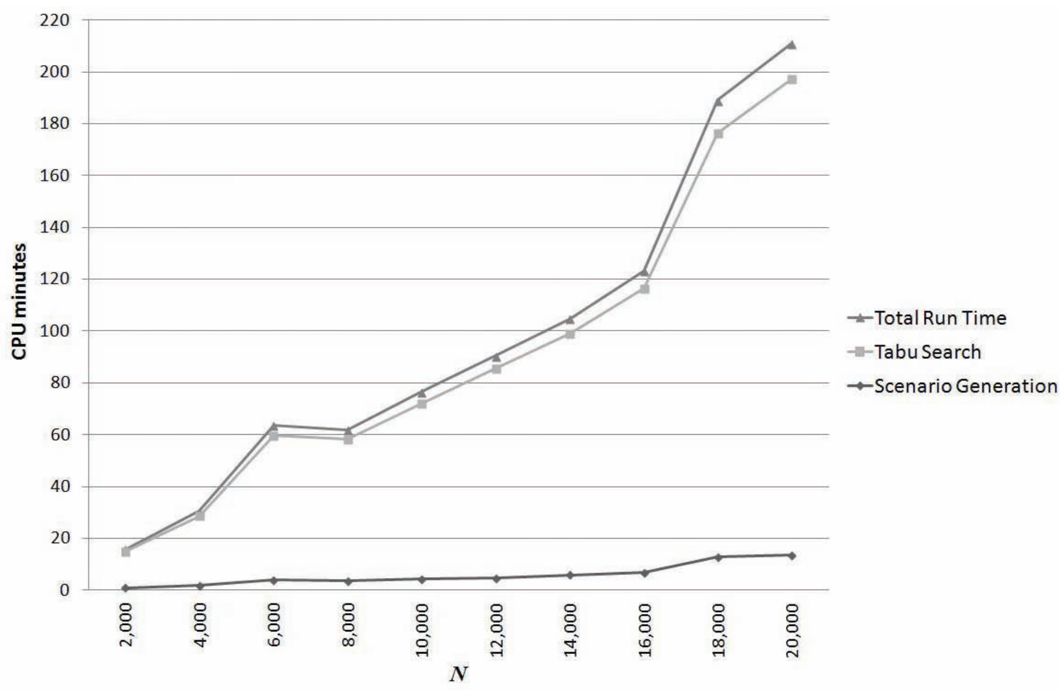


Figure 6: Total run time and required times for scenario generation and tabu search as N varies for the DF case

Table 3 shows that the average number of failed links, F, in the IF case is nearly half of that in the DF case. On the average, 36.94% of links fail in the DF case, whereas 19.32% do in the IF case. As a result, the expected demand coverage calculated by the tabu search algorithm for the IF case is larger than that of DF case. However, we also evaluate the best solutions proposed for IF and NF cases using *the DF scenarios* to simulate the post-disaster network more realistically. As the results in Table 3 demonstrate, the percentage of expected covered demand, $\%C$, of the solution obtained from the no failure scenario is (on the average) 19% smaller than $\%C$ of the best solutions found with DF scenarios. This shows that ignoring network vulnerability in the facility location decisions may cause significantly inferior service after an expected earthquake. While considering possible link failures gives better solutions, *how* the links fail makes a difference. If a solution is obtained according to IF case, then on the average 8% less demand can be covered compared to a solution found with DF case. The unrealistic assumption of independent link failures may cause poor service level in the actual situation.

6.3 Analysis on the number of ERFs to open

We next investigate the effect of the number of open ERFs, Q, on the percentage of covered demand, $\%C$, using parameters $N = 10,000$, $W = 15$ km, and $R = 15$ km. Figure 7 illustrates the change in $\%C$ for $Q = 1, 2, \ldots, 13$ for DF, IF, and NF cases.

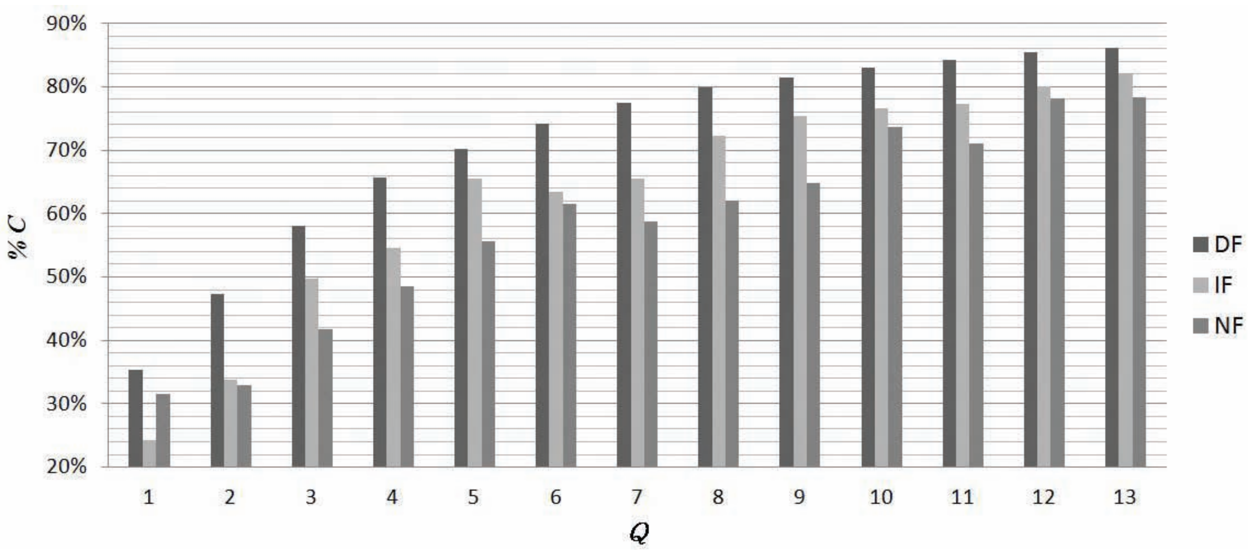


Figure 7: $\%C$ for varying Q for DF, IF, and NF cases

According to Figure 7, while having more facilities increases the expected percentage of demand covered in all cases, after $Q = 8$, $\%C$ does not increase significantly. Since opening a new ERF requires considerable efforts and costs, IMM would decide to open a new ERF only if there is a high marginal benefit of opening another ERF in terms of percentage of covered demand. Figure 8 provides the marginal benefit of opening a new ERF in terms of percentage of covered demand for $Q = 1, 2, \ldots, 12$ for the DF case. According to the figure, the marginal benefit is not larger than 1% for $Q > 8$. Hence, we set $Q = 8$ in our analysis.

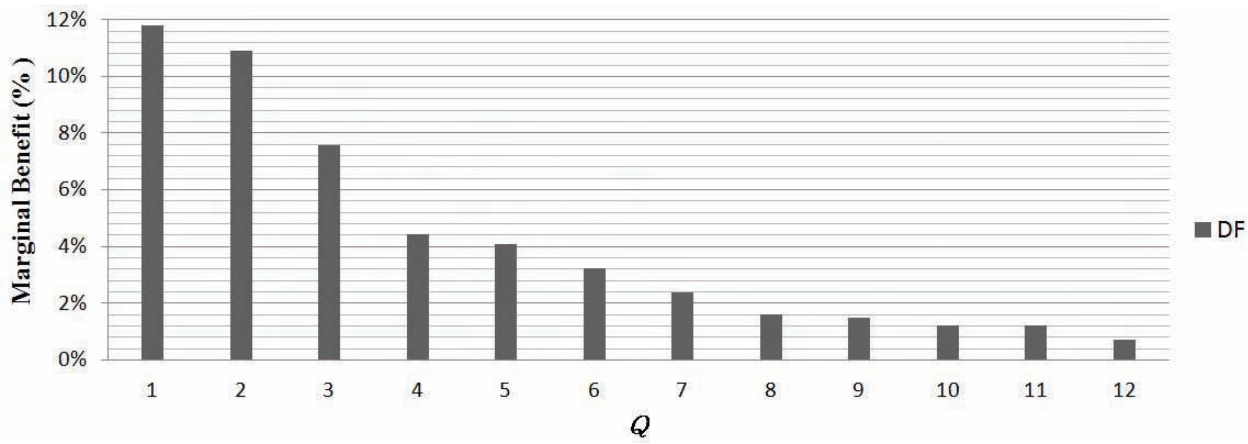


Figure 8: Marginal benefit of opening a new ERF for varying Q in the DF case

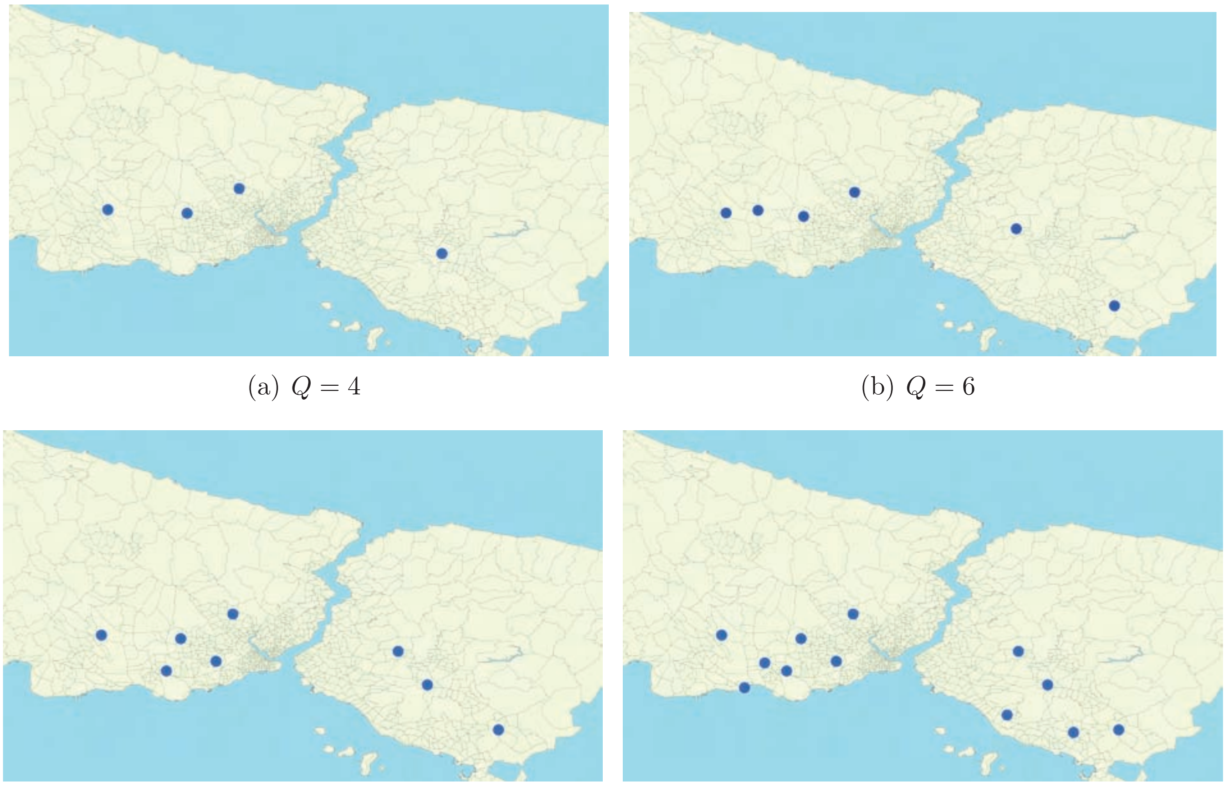
In Figure 7, we also observe that when the network is assumed to be totally reliable, i.e., in the NF case, the percentage of demand coverage is considerably smaller than that of the unreliable case (by nearly 8% even for $Q = 13$). Again, this illustrates how assuming reliability might lead to misleading demand coverage expectations for unreliable networks.

In addition, we show the open ERF locations for varying Q in Figure 9. When $Q = 4$, three of the ERFs are located in the more populated European side of the city. When Q increases to 6, one more facility is located on each side of the Bosphorus straight. For the remaining cases, the number of open ERFs in Europe is two more than that in Asia. When $Q = 12$, three ERFs are located close to each other in the most risky southern part of the European side.

6.4 Analysis on the coverage distance limit

In our model, a demand point i is covered by a facility at j in scenario s if and only if there exists at least one path among the surviving alternative paths between i and j with length of at most the distance limit, R. Clearly, R is closely correlated with the targeted service level in case of a disaster. By setting R between 5 and 30 km, the demand coverage changes as reported in Table 5 in DF, IF, and NF cases for $Q = 8$ and $W = 15$ km.

In Table 5 we see a dramatic increase in demand coverage as R increases from 5 to 15



(a) $Q = 4$ (b) $Q = 6$

(c) $Q = 8$ (d) $Q = 12$

Figure 9: Open ERFs for varying Q in the DF case

km in all cases. Under the assumption of a reliable network, coverage percentage, $\%C$, reaches almost 68% with $R = 15$, whereas considering unreliability of the links leads to 80% coverage. As R increases beyond 15 km, $\%C$ also increases but not significantly in all cases. Based on this observation and that 15 km is a realistic distance to provide a reasonably well service quality in a disaster situation, we set $R = 15$ km in our analysis. We also see in Table 5 that the differences in $\%C$ values between DF and IF cases are larger for small R values.

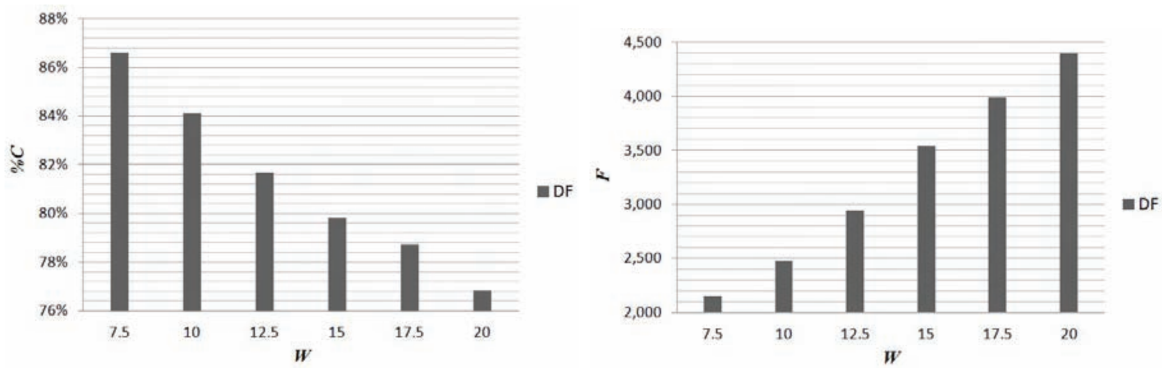
6.5 Analysis on the dependency distance limit

For the DF case, the dependency distance limit, W, determines the list of neighbor links (dependency set) of each link $(i, j) \in A$. Note that a link (i', j') fails if it belongs to the dependency set of a failed link (i, j) that has a stronger survival probability, that is, $p_{i'j'} \leq p_{ij}$. Figure 10(a) illustrates how the percentage of expected demand coverage, $\%C$, decreases as W increases. Figure 10(b) presents the average number of failed links when

Table 5: Analysis on the coverage distance limit for Istanbul's network for Model C

	DF		IF			NF		
R	C	$\%C$	C_{IF}	C	$\%C$	C_{NF}	C	$\%C$
5	42428	21	91221	25721	13	116003	20874	11
10	110608	56	154547	94228	48	176742	86213	44
15	157522	80	174566	136939	69	178644	134858	68
20	179975	91	187301	177129	90	192810	159579	81
25	187334	95	192599	181598	92	193540	177403	90
30	191076	97	193796	189370	96	193540	181882	92
Total Number of Links: 9,578					Total Demand: 197,342			

$W = \{7.5, 10, \ldots, 20\}$ km with $Q = 8$ and $R = 15$ km.



(a) $\%C$ (b) F

Figure 10: Change in $\%C$ and F for varying W in the DF case

According to Figure 10(a), $\%C$ decreases almost linearly with W since the number of failed links increases with W in a similar fashion, as shown in Figure 10(b). As W gets larger, the number of alternative surviving paths that are shorter than R km becomes smaller and as a result, the expected demand that can be covered reduces.

As stated in Section 5.1.3, the survival probability of the links are between 0.7 and 0.9 for Model C. Considering the worst-case scenario, we set $W = 15$ km in our analysis since in that case the percentage of average number of failed links is near 70.

In Figure 11, we visualize the distribution of expected coverage percentage of the demand points geographically, with respect to the open ERFs in the DF case when $W = 15$. In the figure, squares indicate demand points and are colored such that the dark green ones have the highest and the dark red ones have the lowest coverage percentages. In the solution, 18 demand points in dark red that are away from all open ERFs have zero coverage. However, these demand points constitute only 10% of the total demand. All of the remaining demand points have above 48% expected coverage, whereas only 23 demand points (out of 186) have less than 60% expected coverage. That is, 12.4% of the demand points are expected to have low coverage but their demand adds up to 15.5% of the total demand. On the other hand, all of the yellow, orange and red demand points (which constitute 65% of the demand points) have more than 90% coverage.

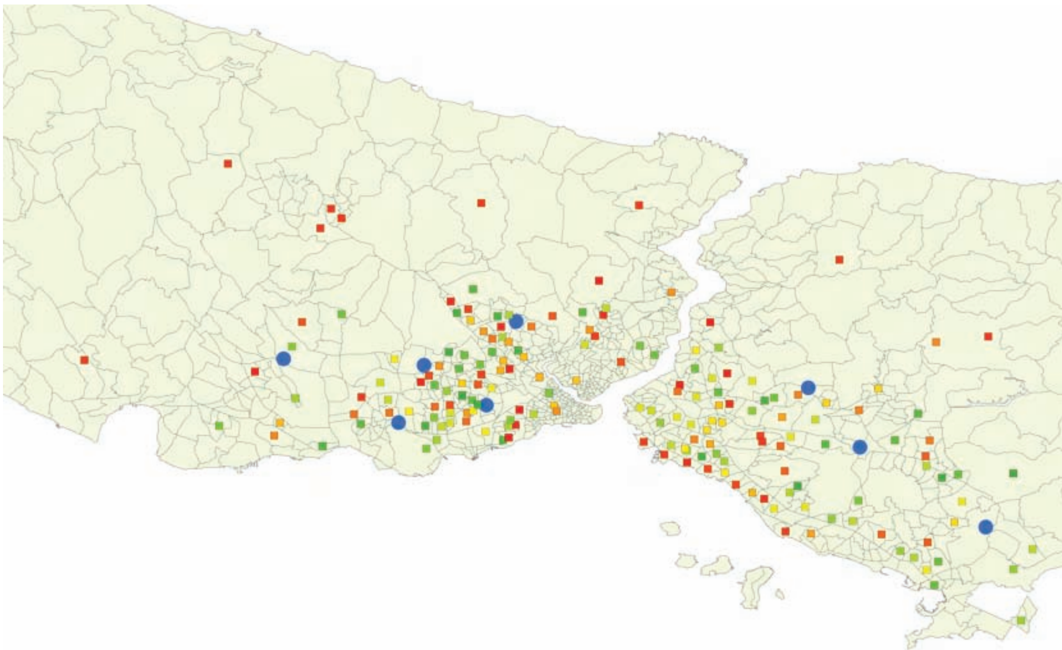


Figure 11: Open ERFs and expected covered demand distribution when $W = 15$ km in the DF case (Green: high values, Red: low values)

Figures such as Figure 11 provide a visual guideline to the decision-makers as they illustrate the distribution of the service level throughout the city and could also be used to observe the equity of the service level. Figures 3 and 11 together reveal that, in general, regions where demand is concentrated get a high service level. However, vulnerable roads adversely affect the service level at highly risky areas. The solution captures this by means of path reliability. Figure 11 also depicts the areas which are expected to get a low service level. Some of the demand points with low expected coverage percentage are in fact close to an open ERF. Moreover, several demand points in almost same proximity to an ERF have different service levels. This may be attributed to the differences in the availability of alternative paths and their reliability.

While Figure 11 illustrates the service level for each demand point, 12 presents the distribution of the expected service level in aggregate. It shows what percentage of total demand receives what range of service level, i.e. expected coverage percentage, $C\%$ over the generated scenarios. According to the results, 62% of the demand is expected to be serviced by a facility within 15 km, in at least 90% of the scenarios.

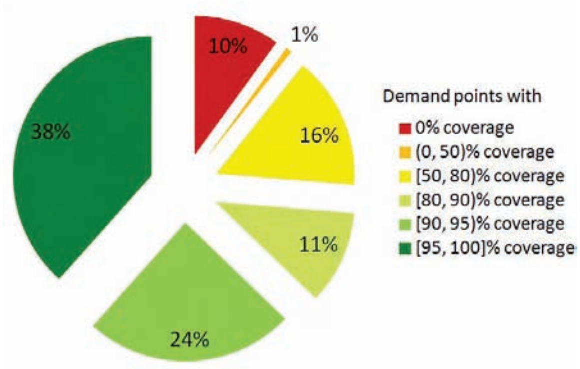


Figure 12: Expected coverage distribution of total demand when $W = 15$ km in the DF case

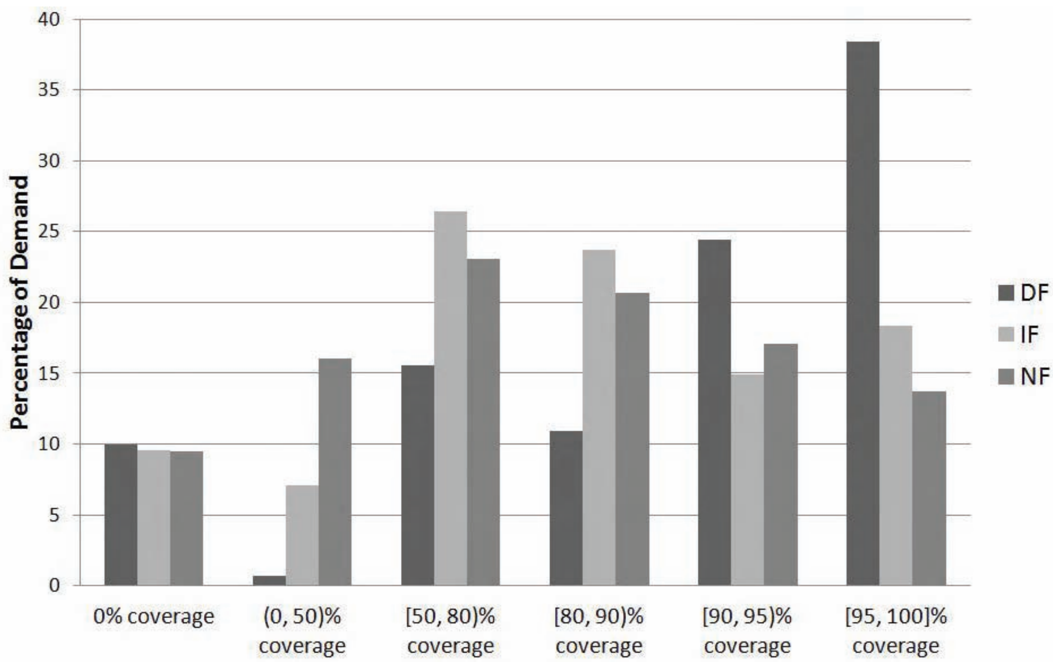


Figure 13: Distribution of total demand according to expected percentage coverage (DF, IF, and NF cases with $W = 15$ km)

We also compare the solutions obtained by DF, IF and NF cases in terms of the distribution of the expected service level. Figure 13 shows that the DF solution dominates the others in service level by a large margin. In fact, the DF solution services around 30% of total demand with a better $C\%$, compared to the IF solution.

7 Conclusions

We provide a practical optimization method to select the locations of emergency response facilities in the pre-disaster stage. The method takes the vulnerability of the transport network into consideration explicitly. We first generate a set of paths from each potential facility location to each demand point. Then, we assign a survival probability to each link of the network according to the risk level of the region under an expected disaster scenario. We select facility locations to maximize the total expected demand covered within a specified distance limit by a tabu search algorithm. The algorithm utilizes a sample average method to estimate the objective function value within the search procedure.

We compare the solutions obtained with the proposed approach under: (i) independent link failures (IF), (ii) dependent link failures (DF), and (iii) no link failure (NF). We aim to capture the impact of the disaster by a novel Distance-Based link dependency (*DB-dependency*) model. Each edge is negatively influenced by edges within a distance limit to it. The dependency condition is defined such that the failure of a link implies the failure of all links with smaller probability of survival.

We have applied our approach to Istanbul's network, which is under a high earthquake risk. We have constructed a large-scale network with 267 nodes and 9,587 links with real road distances and generated link survival probabilities by considering the vulnerability of the corresponding road segments to seismic hazard. We have run the tabu search algorithm with 10,000 scenarios, which is significantly higher when compared to the sample sizes considered in previous studies in humanitarian logistics.

We compare solutions obtained by the IF, DF, and NF cases under various parameter configurations. We observe that the performance of IF and NF solutions by simulating the post-disaster network with respect to DF. DF solutions achieved significantly higher expected coverage in all parameter settings, compared to IF and NF solutions. Our analysis shows the benefits of incorporating (i) link failures and (ii) dependencies among link failures, to facility location decisions in relief aid supply chain design. We can deduce the following insights:

- Ignoring link failures in facility location decisions leads to sub-optimal solutions and consequently, poor service levels when links fail and some of the paths become blocked after a disaster.

- When probabilistic link failures are considered, assuming links fail independently results in unrealistic and optimistic expectations of network resilience and service level. Therefore, the selected facility locations are likely to provide poor service to demand points that are accessed via unreliable paths, especially when paths contain unreliable links in close proximity to each other. This creates regional unfairness, which is an undesired outcome in public service.

- Our distance-based dependency scheme gives a more realistic and pessimistic estimation of post-disaster network conditions by increasing simultaneous failures. As such, it can be used to understand performance in worst-case situations and guide risk-averse decision makers. In fact, many government and non-governmental agencies are fundamentally risk-averse in their mandate, especially when the objective is disaster preparedness.

- Simulating the post-disaster road conditions by our approach within the heuristic search results in significant improvements in reachability to demand points compared to the independent link failure case, when evaluated under pessimistic scenarios with correlated failures.

- The dependency level can be controlled by the distance parameter. Therefore, the method can be tailored with respect to risk preferences of the decision makers and spatial impact levels in different disaster types. In the earthquake case, the wave propagation of seismic hazard from the epicenter is captured in survival probabilities and by means of the distance limit.

We observe that the proposed framework, which incorporates dependencies among link failures and alternative path availability, provides robust solutions under various parameter settings. The proposed heuristic algorithm runs in a very short computation time, even for a large-scale network such as the Istanbul network; hence proving its practicality. In conclusion, we suggest that the proposed heuristic can be useful in a decision support tool to guide facility location decisions in preparation for a large-scale emergency.

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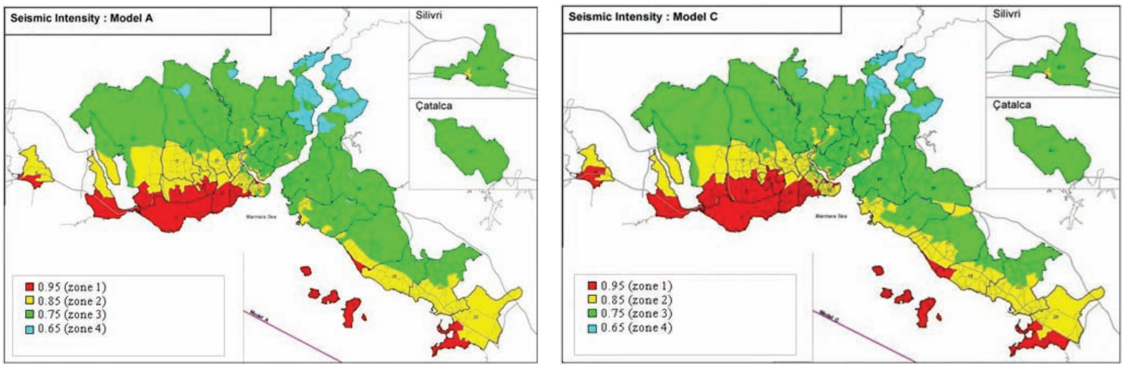
A Notation

Π_{ji}	set of k alternative paths between potential ERF location j and demand point i
π_{jip}	alternative path p in Π_{ji}
l_{jip}	distance of π_{jip}
R	coverage distance limit
s	a scenario in set S
a_{ij}^s	1, if link (i, j) survives in scenario s, 0, otherwise.
z_i^s	1, if demand point i is covered by an ERF in scenario s, 0, otherwise.
F	average number of failed links in scenario set S
r	a random number between 0 and 1
R	coverage distance limit (km)
W	dependency distance limit (km)
Q	maximum number of ERFs to open
y	current solution
y'	a neighboring solution
y^*	best found solution
$C(y)$	objective value, i.e., expected demand coverage, of solution y
$\%C$	percentage of covered demand
θ	tabu tenure
η	total number of iterations allowed

B Seismic zones of Istanbul



(a) for Model A (b) for Model C

Figure 1: Seismic zone classification of Istanbul in JICA report