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Pre-positioning of relief items under road/facility vulnerability with concurrent restoration and relief transportation

Abstract

Planning for response to sudden-onset disasters such as earthquakes, hurricanes, or floods needs to take into account the inherent uncertainties regarding the disaster and its impacts on the affected people as well as the logistics network. This paper focuses on the design of a multi-echelon humanitarian response network, where the pre-disaster decisions of warehouse location and item pre-positioning are subject to uncertainties in relief item demand and vulnerability of roads and facilities following the disaster. Once the disaster strikes, relief transportation is accompanied by simultaneous repair of blocked roads, which delays the transportation process, but gradually increases the connectivity of the network at the same time. A two-stage stochastic program is formulated to model this system and a sample average approximation (SAA) scheme is proposed for its heuristic solution. To enhance the efficiency of the SAA algorithm, we introduce a number of valid inequalities and bounds on the objective value. Computational experiments on a potential earthquake scenario in Istanbul, Turkey show that the SAA scheme is able to provide an accurate approximation of the objective function in reasonable time, and can help drive policy-based implications that may be applicable in preparation for similar potential disasters.

Keywords: Disaster preparedness; inventory pre-positioning; relief transportation; network restoration; stochastic programming; sample average approximation

1 Introduction

In the aftermath of large-scale disasters such as earthquakes, hurricanes, and floods, effectiveness of the response activities is generally measured in terms of timeliness. When the transportation of relief commodities (e.g., food supplies, tents, blankets, hygiene kits) to the beneficiaries is concerned, a timely delivery requires the availability of supplies, quick mobilization of transportation resources, and an efficient scheduling of visits to the beneficiaries. Planning of these activities is generally carried out well in advance of an expected disaster, during the preparedness stage. To ensure the availability of relief commodities, local communities and non-governmental organizations generally make use of two methods: post-disaster procurement from local/international vendors or pre-positioning of supplies in anticipation of the disaster (Balçık and Beamon, 2008). Acquisition of commodities in the disaster aftermath has the advantage of more accurate information regarding the needs of the beneficiaries, thereby avoiding the possibility of stockouts or holding excessive inventory. However, such transactions are generally more costly, and the commodities may not become available within the critical response time period, where failure to respond to the beneficiaries' needs in a timely manner may increase the loss of life, detriment the well-being of the population, and inflict even more damages on the infrastructure. Pre-positioning of relief items in locations within close proximity of potential disaster areas not only eliminates the need for expensive post-disaster procurement, but also ensures their availability in the immediate aftermath of the disaster (Duran et al., 2011). Perhaps the best-known application of inventory pre-positioning at the global level is the United Nations Humanitarian Response Depots (UNHRD), which is managed by the World Food Programme, and consists of six depots that carry out the procurement, storage, and transportation of relief commodities whenever needed (UNHRD, 2017).

Design of an inventory pre-positioning network generally involves the decisions of where to locate the relief facilities, as well as what types and how much of relief commodities to store in each of these facilities. These decisions are subject to risks brought about by the location, magnitude, and timing of the potential disaster, which lead to lack of precise information on the availability of the commodities, condition of the relief facilities, status of the transportation vehicles and infrastructure, and the demand. Failure to incorporate such risks when designing a pre-positioning network may result in the shortage or excessive storage of the commodities, under- or over-investment on the facilities, and ineffective or even infeasible relief transportation in the aftermath of the disaster.

In addition to their catastrophic effects on the population, large-scale sudden-onset disasters also result in substantial damages to the response logistics infrastructures. The damage can occur in the form of collapsing road networks and bridges, blockage of roads by the debris generated by the disaster, or damages on the critical facilities, such as warehouses or vehicle dispatch locations. Examples from recent disasters shed light into the extent of the costly and complicated effects of such damages. For Hurricane Katrina (2005), cleanup of the resulting debris accounted for around 27% of all disaster-related costs, whereas the total economic damage on the infrastructure inflicted by Hurricane Sandy is estimated to be US$33 billion. During the Haiti earthquake (2010) and Typhoon Haiyan (2013), although supplies were available for distribution to the beneficiaries, damage in the road infrastructure either delayed or prevented their deliveries (Çelik, 2016). More recently, after Hurricane Maria (2017) hit through Puerto Rico, supplies in the port of San Juan were stuck due to a shortage of truckers and the island's devastated infrastructure (Gillespie et al., 2017). Within the context of inventory pre-positioning, incorporation of the potential road damage into network design is made more difficult by the fact that due to the aforementioned uncertainties regarding the disaster, the set of roads that will not be usable and the extent of damage on the affected roads cannot be exactly known in advance. Thus, modeling of road damage needs to take into account the vulnerability of each road segment and the stochastic nature of which segments will become damaged when addressing the decisions of facility location and relief item storage in the disaster preparedness stage.

Availability of the road network infrastructure plays a crucial part in determining the effectiveness of important response activities including relief transportation and search-and-rescue. For this end, one of the first activities carried out in the immediate aftermath of a large-scale disaster is the restoration/repair of the damaged road segments, which generally takes place concurrently with the ongoing response operations. As noted by Çelik (2016), in communities where road recovery and relief transportation are managed or coordinated by the same entity (such as the local municipality of a region), integrated planning and scheduling of these activities may lead to significant improvements in the timeliness of the deliveries, which is also applicable to the case of inventory pre-positioning. To the best of our knowledge, only one study (Wisetjindawat et al., 2015) in the pre-positioning literature considers the coordination of the efforts in these two activities, but does so only by considering ongoing road repair as constraints on the availability of roads, rather than as part of the decision making mechanism. Hence, even though road vulnerability has been included in the design of humanitarian relief pre-positioning networks, there exists an important gap in the literature on the incorporation of road recovery into the network design process.

The effectiveness of a post-disaster relief aid delivery can be measured in terms of a number of factors. These include (1) efficiency, which is the extent at which resources such as equipment, workforce, or budget are used to carry out the distribution, (2) efficacy, i.e., how quickly and accurately the aid is received, and (3) equity, which measures the disparity among the beneficiaries in terms of when deliveries are received (Huang et al., 2012). The choice of what type of objective(s) to use in the modeling process may substantially affect the resulting decisions. Furthermore, definition and modeling of an accurate equity measure is often not straightforward, and its inclusion generally leads to a trade-off with the two other factors. For humanitarian pre-positioning network design, the analysis of objective function selection and of the trade-offs may have important managerial implications, which forms another point of focus for this paper.

This paper considers the problem of designing a three-echelon humanitarian inventory pre-positioning network by taking into account the potential damages to the road segments and concurrent road repair during relief transportation. To incorporate the uncertainties regarding the effects of the disaster on demand and damage to the network, we propose a two-stage stochastic programming formulation, in which the first-stage involves warehouse location and inventory pre-positioning decisions, whereas road repair and relief transportation decisions are made in the second stage, following the onset of the disaster. Prior to the disaster, potential damage to each road segment is estimated based on a probability distribution. As the number of potential road damage and demand scenarios makes it impossible to solve the two-stage stochastic programming model optimally, we develop a sample average approximation (SAA) scheme to find near-optimal solutions. Since the SAA depends on solving a large-scale mixed-integer program and may fail to be applicable for large-scale instances due to computational burden, we introduce a number of valid inequalities by making use of the structural properties of the problem. The effectiveness of the SAA procedure as well as that of the valid inequalities are assessed using preliminary experiments. Bounding the efficiency of the delivery operations by a budget, we define alternative objective functions for efficacy, equity, and robustness, and analyze the trade-off among these objectives in terms of objective function values and solution structure. To the best of our knowledge, this is the first study in the literature that considers road repair and relief transportation as part of the post-disaster decision making process and that evaluates the effects of using different objectives in doing so. Making use of a set of instances based on a potential earthquake in Istanbul, we assess the computational performance of the SAA approach, evaluate the effects of involving road-repair in conjunction with relief transportation, compare the performance of models using different objective functions (efficacy vs. equity vs. robustness) with regard to one another, and exemplify how policy-based implications can be drawn using the proposed models in this paper.

The remainder of this paper is organized as follows: Section 2 presents a literature review on inventory pre-positioning, relief transportation under road damage and repair, and incorporation of equity into routing models in humanitarian logistics. In Section 3, we provide a formal definition of the problem and the two-stage stochastic programming model, followed by a summary of the SAA scheme and the set of valid inequalities used to strengthen the SAA approach. Section 4 discusses the case study on a potential earthquake in Istanbul, as well as the results of the experiments in the context of aforementioned research questions. We conclude the paper in Section 5 and point to potential future research areas regarding this study.

2 Literature Review

The increasing number and complexity of natural and human-inflicted disasters as well as long-term development issues have led to more complex needs for relief in response to these events. Since around 80% of all humanitarian relief efforts can be attributed to logistics (Trunick, 2005), there has also been an increasing level of awareness for the importance of humanitarian logistics. Within the last decade and a half, operations research (OR) and management science (MS) have provided a vast number of contributions to humanitarian logistics, analyzed in a number of review papers and tutorials, including Altay and Green (2006), Caunhye et al. (2012), Çelik et al. (2012), Galindo and Batta (2013), Özdamar and Ertem (2015), and Kara and Savaşer (2017). Reviews on more relevant aspects to the work in this paper are Faturechi and Miller-Hooks (2015), which presents a framework for measuring the performance of transportation infrastructure networks before and after disasters, and Çelik (2016), which provides an extensive review of studies regarding transportation network and infrastructure restoration in humanitarian operations. Within the realm of this literature, our work may be considered on the intersection of inventory pre-positioning, concurrent post-disaster network repair/recovery and relief distribution, and consideration of equity in relief routing.

The studies on inventory pre-positioning may differ in terms of whether uncertainty is incorporated into the modeling process, which additional decisions are included (e.g., facility location, relief distribution), the main objective(s), solution methods, and additional constraints (e.g., minimum service levels, limits on number of facilities, road capacities). While a majority of those involve the inherent disaster-related uncertainties, there nevertheless exists a limited number of papers with the assumption that all parameters of the problem are known in advance. The use of a deterministic approach facilitates the incorporation of aspects such as the consideration of a more complicated cost structure

(Khayal et al., 2015), involvement of other decisions in the preparedness phase (Rodríguez-Espíndola et al., 2018), and the existence of multiple conflicting objectives (Görmez et al., 2011; Abounacer et al., 2014; Barzinpour and Esmaeili, 2014; Rodríguez-Espíndola and Gaytán, 2015).

In the literature, uncertainties on the inventory pre-positioning problem have been traditionally modeled as two-stage stochastic programs, where the facility location and pre-positioning decisions are made in the pre-disaster stage, and relief transportation decisions are made after the disaster hits, when the uncertainty is resolved. Table 1 provides an overview of recent inventory pre-positioning papers involving uncertainty of at least a subset of parameters. Among the reviewed papers, a vast majority considers the minimization of total expected relevant costs, which may include facility location, inventory pre-positioning, outsourcing, transportation, unmet demand, and surplus of commodities. A limited number of studies (Balçık and Beamon, 2008; Salmerón and Apte, 2010; Duran et al., 2011; Noyan et al., 2016; Klibi et al., 2018; Turkeš et al., 2017; Noham and Tzur, 2018) focus on demand-related measures, such as maximizing satisfied demand, minimizing maximum unsatisfied demand over all locations, or minimizing total/maximum response time. In this paper, motivated by the real-life application, we take the latter approach and center our attention on the service times of the beneficiaries, while limiting our costs by predetermined budgets.

Disregarding Wisetjindawat et al. (2015), all studies in Table 1 incorporate the uncertainty in relief demand and/or supply. Furthermore, almost all of the papers involve the uncertainty in at least one of travel time, transportation cost, or road capacity as well. In this paper, we treat relief demand and travel times as uncertain. However, our models can be easily adjusted to incorporate the uncertainty in transportation costs.

With few exceptions, most papers in Table 1 consider the uncertainty in the damage to the road network, albeit in three different ways: (i) by correlating the damage level with uncertain travel costs (Balçık and Beamon, 2008; Rawls and Turnquist, 2010, 2011, 2012; Bozorgi-Amiri et al., 2013; Pacheco and Batta, 2016; Torabi et al., 2018), (ii) by inflating the travel times based on the damage level, (Mete and Zabinsky, 2010; Salmerón and Apte, 2010; Davis et al., 2013; Rezaei-Malek et al., 2016; Tofighi et al., 2016; Başkaya et al., 2017; Elçi and Noyan, 2018), and (iii) by deflating the capacities of each road segment depending on the damage level (Rawls and Turnquist, 2010, 2011, 2012; Hong et al., 2015; Noyan et al., 2016). Lastly, the approach by Renkli and Duran (2015), Wisetjindawat et al. (2015), and Alem et al. (2016) assumes that each path between a supply-demand node pair has a certain probability of being completely blocked (not traversable at all). In this paper, since the main concern relates to the timeliness of relief delivery activities, we follow the second approach and translate the road damage into uncertainties in travel time. However, based on discussions with the stakeholders, we assume that if the damage level on a road segment exceeds a certain threshold, it is no longer traversable, thereby incorporating the possibility of binary damage into our models.

Applications in the post-disaster network repair and recovery literature include road restoration, repair of power and

Table 1: An overview of recent studies on humanitarian inventory pre-positioning involving uncertainty

	Objectives			Uncertain parameters				Modeling of road damage				
Reference	Cost based	Coverage based	Other	Demand/ Supply	Travel time	Tran. cost	Road capacity	Travel time	Tran. cost	Capacity decrease	Binary	Inclusion of repair
Balçık and Beamon (2008)		✓		✓		✓			✓			
Mete and Zabinsky (2010)	✓			✓		✓		✓				
Rawls and Turnquist (2010)	✓			✓		✓			✓	✓		
Salmerón and Apte (2010)		✓	✓	✓	✓			✓				
Duran et al. (2011)		✓		✓								
Rawls and Turnquist (2011)	✓			✓		✓			✓	✓		
Rawls and Turnquist (2012)	✓			✓		✓			✓	✓		
Bozorgi-Amiri et al. (2013)	✓			✓		✓			✓			
Davis et al. (2013)	✓			✓	✓			✓				
Hong et al. (2015)	✓			✓			✓			✓		
Renkli and Duran (2015)			✓	✓			✓				✓	
Wisetjindawat et al. (2015)	✓						✓				✓	✓
Alem et al. (2016)	✓		✓	✓			✓				✓	
Caunhye et al. (2016)	✓			✓	✓			✓				
Noyan et al. (2016)		✓	✓	✓			✓			✓		
Pacheco and Batta (2016)	✓			✓		✓			✓			
Paul and MacDonald (2016)	✓			✓	✓		✓	✓				
Rezaei-Malek et al. (2016)	✓			✓	✓			✓				
Tofighi et al. (2016)	✓			✓	✓			✓				
Başkaya et al. (2017)			✓	✓	✓			✓				
Chen et al. (2017)	✓			✓								
Klibi et al. (2018)	✓	✓		✓	✓			✓				
Manopiniwes and Irohara (2017)	✓			✓	✓			✓				
Turkeš et al. (2017)	✓	✓		✓	✓			✓				
Elçi and Noyan (2018)	✓			✓	✓			✓				
Noham and Tzur (2018)		✓		✓								
Torabi et al. (2018)	✓			✓		✓			✓			
This study		✓		✓	✓			✓			✓	✓

telecommunications networks, clearance of post-disaster debris, and snow removal (Çelik, 2016). When considered in terms of how network restoration is performed in relation to relief transportation, studies in this area can be categorized into three groups: (1) studies on network recovery that implicitly aim at an effective relief delivery while not modeling it explicitly (Matisziw et al., 2010; Maya Duque and Sörensen, 2011; Aksu and Özdamar, 2014; Özdamar et al., 2014; Maya Duque et al., 2016; Akbari and Salman, 2017), (2) those that explicitly model relief transportation, but assume that the delivery process is performed after network restoration is complete (Wang and Hu, 2007; Wang and Chang, 2013; Berktaş et al., 2016; Ransikarbum and Mason, 2016), and (3) papers that consider these two activities in conjunction with each other (Çavdaroğlu et al., 2013; Nurre and Sharkey, 2014; Çelik et al., 2015; Xu and Song, 2015; Sekuraba et al., 2016). Our work falls into the third group of studies in this stream. While these papers solely focus on the post-disaster decisions, our paper contributes to this literature by integrating the pre-disaster facility location and inventory pre-positioning decisions with post-disaster network repair.

In the inventory pre-positioning literature, very limited consideration is given to network repair/restoration. To the best of our knowledge, Wisetjindawat et al. (2015) is the only paper to incorporate these decisions together. However, in doing so, network repair is assumed as exogenous, i.e., network repair is only included as increasing network availability. We take a step further and consider road restoration as part of the decisions. Although this complicates the modeling and solution process, it has potential to improve the effectiveness of pre-positioning and relief transportation.

The focus on the well-being of beneficiaries in humanitarian operations leads to the inclusion of equity (in addition to efficiency and efficacy) in modeling. However, the definition of equity is context-dependent and its inclusion generally leads to a trade-off with efficacy and efficiency, and therefore presents additional modeling challenges. Tzeng et al. (2007), Balçık and Beamon (2008), Beamon and Balçık (2008), Campbell et al. (2008), Huang et al. (2012), Cao et al. (2016) form an almost extensive list in this limited stream of studies for equitable routing. In this paper, we borrow performance measures from these studies and assess their trade-off with efficacy and robustness in our context.

The network design problem in this paper bears close resemblance to the well-known and well-studied location-routing problem (LRP). Interested readers on the LRP are referred to the recent reviews by Prodhon and Prins (2014) and Drexl and Schneider (2015). In our study, we modify a number of valid inequalities from Karaoğlan et al. (2012) and Toyoğlu et al. (2012) to strengthen our formulation. Other recent papers that develop valid inequalities on the LRP include Perboli et al. (2011), Guerrero et al. (2013), Rieck et al. (2014), and Rodríguez-Martín et al. (2014). The LRP has also received widespread application in the humanitarian relief network design literature. Recent examples include Abounacer et al. (2014), Rath and Gutjahr (2014), Rennemo et al. (2014), Moreno et al. (2016), Moreno et al. (2018) and Vahdani et al. (2018). In contrast to the papers in this stream, our problem environment allows us to make use of predetermined routes, thus avoiding the computational burden resulting from subtour elimination constraints.

A recent review of two-stage stochastic programming in disaster management, which is the modeling approach in this paper, is provided by Grass and Fischer (2016). The computational burden of these models increases substantially with the number of scenarios, which can be addressed by sampling over the potential set of scenarios by means of *sample average approximation* (Kleywegt et al., 2001; Shapiro, 2013). Recent applications in the humanitarian logistics literature include Garrido et al. (2015) for flood emergency response, Rodríguez-Espíndola and Gaytán (2015) in preparation for floods, Salman and Yücel (2015) for facility location, and Klibi et al. (2018) for inventory pre-positioning.

The main contribution of this paper arises from the fact that, to the best of our knowledge, it is the first study to consider road repair as part of the post-disaster decisions within the design of an inventory pre-positioning network. When the same entity (e.g., local government or municipality) manages these operations or when coordination among the managing entities is possible, this approach may lead to more timely relief deliveries. Since exact solution of the two-stage stochastic program for large-scale instances is virtually impossible, we provide an SAA scheme and strengthen it with a set of valid inequalities and bounds. Our computational experiments show that when applied on a potential earthquake scenario, this scheme provides an accurate and fast approximation. These experiments also provide examples for cases where integrating potential network repair provides significant improvements.

3 Problem Description and Mathematical Model

In this section, we define the humanitarian pre-positioning network design problem with network restoration, present the corresponding two-stage stochastic programming model, and describe the SAA scheme for its heuristic solution, along with the valid inequalities and bounds on the objective value. While our specific consideration of the problem (regarding the network structure and how road damage is considered) is mainly based on our collaboration and discussions with the Istanbul Metropolitan Municipality (IMM), our problem definition can be extended to other network structures and road damage scenarios without significant additional effort.

3.1 Humanitarian Pre-Positioning Network Design with Concurrent Road Restoration and Relief Distribution

In anticipation of a potential large-scale sudden-onset disaster, a pre-positioning network generally consists of a number of *warehouses*, where different types of relief commodities are stored, a set of *distribution centers* (DCs), which serve as consolidation points for items before they are transported to the *demand locations* (DLs). In the case of Istanbul, such a three-echelon network has been proposed in both Japan International Cooperation Agency (2002) and Metropolitan Municipality of Istanbul (2003), where the warehouses are to be located among a set of candidate locations, and the DCs are to be designed by the renovation and reorganization of public buildings such as schools, libraries, etc.

Once the disaster hits, it triggers partial or complete damage on the road network as well as the facilities. A partially

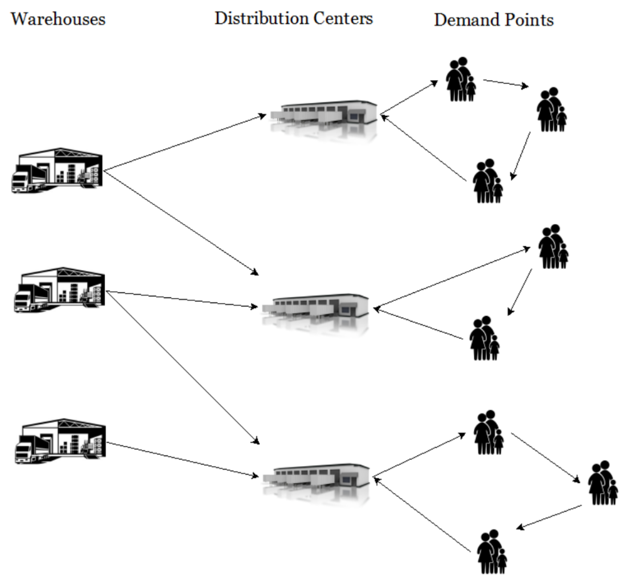

Figure 1: The proposed three-echelon inventory pre-positioning network

damaged road segment incurs longer travel time due to the congestion on it, whereas a complete damage implies that the road is not traversable.

Immediately following the onset of the disaster, the IMM plans to conduct the subsequent rapid needs assessment by means of volunteers, unmanned air vehicles, and social media to assess the status of the road network and the need for relief items. This assessment is followed by two activities, which are performed in concurrence with each other. To satisfy relief item demand, truckloads of relief items will be transported to the DCs, from where each outgoing truck will visit a number of DLs in order to distribute the items. To ensure coordination of deliveries, trucks leave each DC at a pre-determined dispatch time. Simultaneously, repair teams are dispatched to recover part of the damaged road network, so that relief distribution and search-and-rescue can proceed in a more timely manner. These two activities may overlap when relief distribution vehicles need to traverse road segments with ongoing recovery, in which case they will have to wait for full recovery of the segment before proceeding. The three-echelon inventory pre-positioning network is illustrated in Figure 1.

In the case where the amount of pre-positioned items is not sufficient to satisfy the overall demand for a commodity, the IMM aims to outsource items to the warehouses (at a higher cost). Network design operations in the pre-disaster stage and the post-disaster activities of relief transportation, road restoration, and outsourcing are subject to separate pre-determined budgets.

3.2 A Two-Stage Stochastic Programming Model

To incorporate the uncertainty on the demand and network damage, we model the pre-positioning network design problem with concurrent road restoration and relief distribution as a two-stage stochastic mixed integer program. The index sets, deterministic and stochastic parameters, and the first- and second-stage decision variables are summarized in Table 2. Before we proceed with the details of the modeling approach, we list the assumptions used in the model.

- Potential disaster scenarios occur independently of each other.
- Instead of optimizing among all possible routes, we make use of a predetermined subset of routes and choose from among these.
- There exist separate budgets for the pre- and post-disaster phases, which is in line with Metropolitan Municipality of Istanbul (2003)
- As aforementioned, based on planned practice, the dispatch trucks have to wait until a predetermined dispatch time to leave a DC, mainly for coordination purposes.
- No damage is assumed for warehouses, as these are designed to withstand high-impact earthquakes. We only consider complete damage (where no items can be consolidated in the facility) or no damage to the DCs, due to our discussions with the IMM. However, these are both without loss of generality; the model can be easily extended to incorporate partial damage and warehouse damage.
- A road segment may be partially or completely damaged. A partially damaged road incurs additional travel time, due to its decreased capacity; whereas a completely damaged road does not allow traversal over it. Once repaired, a road incurs its pre-disaster travel time.
- Demand and damage information is made available before repair and relief distribution starts. This assumption is in line with the inventory pre-positioning literature, and is made possible by immediate needs assessment activities and satellite/UAV imagery of the road network.
- A delivery route cannot be used if at least one of its segments is completely damaged.
- A given DL can be served a given commodity from a single DC, in order to avoid coordination issues.
- Teams start repairing the network at the same time relief distribution starts. Whereas this may be a strong assumption for more general cases of this problem, the IMM has pre-positioned sufficiently many teams in its districts to ensure all neighboring routes may start to be repaired immediately, if needed. As this is the first study to tackle the problem of incorporating integrated network repair and relief distribution into inventory pre-positioning, this assumption helps simplify the solution of the problem and understand its structure.

Table 2: Notation

	Index sets
I	Potential warehouse locations
J	Potential DC location
D	Demand nodes
K	Relief commodities
R	Pre-determined delivery routes
R_j	Routes starting from DC $j \in J$
D_r	Demand nodes on route $r \in R$
ξ	Random realizations for network damage and demand
	Deterministic parameters
f_i^1	fixed cost to open warehouse $i \in I$
f_j^2	fixed cost to open DC $j \in J$
p_{ik}	unit pre-positioning cost for commodity $k \in K$ in warehouse $i \in I$
o_{ik}	unit outsourcing cost for commodity $k \in K$ in warehouse $i \in I$
$\tilde{t}_{ij}^1$	travel time on an undamaged road between warehouse $i \in I$ and DC $j \in J$
$\tilde{t}_{jd}^2$	travel time on an undamaged road between $j \in J \cup D$ and DL $d \in D$
d_{ij}^1	transportation cost between warehouse $i \in I$ and DC $j \in J$
d_r^2	transportation cost for route $r \in R$
r_{ij}^1	repair cost for the road between warehouse $i \in I$ and DC $j \in J$
r_{jd}^2	repair cost for the road between $j \in J \cup D$ and DL $d \in D$
B_1	budget for first stage
B_2	budget for second stage
c_i^1	capacity for potential warehouse $i \in I$
c_j^2	capacity for potential DC $j \in J$
β_k	unit volume of item $k \in K$
η_j	dispatch time from DC $j \in J$
g_{dr}	whether route $r \in R$ visits DL $d \in D$
	Stochastic parameters
$w_j^1(\tilde{\xi})$	whether DC $j \in J$ is (at least partially) operative under realization $\tilde{\xi} \in \xi$
$w_{ij}^2(\tilde{\xi})$	whether the road between $i \in I \cup J$ and $j \in J \cup D$ is (at least partially) operative under realization $\tilde{\xi} \in \xi$
$t_{ij}^1(\tilde{\xi})$	travel time between warehouse $i \in I$ and DC $j \in J$ under realization $\tilde{\xi} \in \xi$
$t_{jd}^2(\tilde{\xi})$	travel time between $j \in J \cup D$ and DL $d \in J \cup D$ under realization $\tilde{\xi} \in \xi$
$\rho_{ij}(\tilde{\xi})$	repair time for the road between $i \in I \cup J$ and $j \in J \cup D$ under realization $\tilde{\xi} \in \xi$
$\delta_{dk}(\tilde{\xi})$	demand for commodity $k \in K$ at DL $d \in D$ under realization $\tilde{\xi} \in \xi$
	First-stage decision variables
y_i^1	whether warehouse $i \in I$ is open
y_j^2	whether DC $j \in J$ is open
x_{ik}	amount of commodity $k \in K$ prepositioned in warehouse $i \in I$
	Second-stage decision variables
$l_{ij}(\tilde{\xi})$	whether there is a shipment from warehouse $i \in I$ to DC $j \in J$ under realization $\tilde{\xi} \in \xi$
$q_{ik}(\tilde{\xi})$	amount of commodity $k \in K$ outsourced in warehouse $i \in I$ under realization $\tilde{\xi} \in \xi$
$u_r(\tilde{\xi})$	whether route $r \in R$ is used under realization $\tilde{\xi} \in \xi$
$s_{dkr}(\tilde{\xi})$	whether commodity $k \in K$ is sent to DL $d \in D$ on route $r \in R$ under realization $\tilde{\xi} \in \xi$
$\gamma_{ij}^1(\tilde{\xi})$	whether the road from warehouse $i \in I$ to DC $j \in J$ is repaired under realization $\tilde{\xi} \in \xi$
$\gamma_{jd}^2(\tilde{\xi})$	whether the road from $j \in J \cup D$ to $d \in J \cup D$ is repaired under realization $\tilde{\xi} \in \xi$
$\alpha_{dk}^2(\tilde{\xi})$	arrival time of commodities $k \in K$ at DL $d \in D$ under realization $\tilde{\xi} \in \xi$
$\theta_{dr}^2(\tilde{\xi})$	arrival time of route $r \in R$ in DL $d \in D$ under realization $\tilde{\xi} \in \xi$

Among these assumptions, the use of predetermined set of routes as opposed to optimizing over the whole possible set of routes forms a key aspect of our modeling approach. There are mainly three reasons for this assumption. The first is due to the application in practice, where a number of such candidate relief routes (neither of which exceeds four DLs) have already been determined by the Disaster Coordination Center of the IMM. Furthermore, this approach is not limited to our application. As indicated by the guidelines of the International Federation of Red Cross and Red Crescent Societies (International Federation of Red Cross and Red Crescent Societies, 2015), a relief distribution route would normally include no more than five sites to visit. Second, the use of predetermined routes avoids subtour elimination constraints, which would require an extensive amount of computational burden. The third and perhaps the most important reason is that due to the selection of our alternative objective functions, where the aim is to minimize a function of the arrival times at DLs (as opposed to total travel time), the optimal routes tend to include a small number of DLs to visit to balance the arrival times. This is also observed by Huang et al. (2012), where a maximum of five nodes are included in their candidate routes. A discussion of how candidate routes are determined is provided in Section 4.1.

The problem can be modeled on a graph $G = (V, E)$, where the vertices in V consist of the potential warehouse and DC locations (represented by sets I and J), and the demand points (denoted by set D). For our application, the locations refer to districts of a metropolitan city. However, these can immediately be adapted to a regional- or global-level pre-positioning problem. Each warehouse stores relief commodities, indexed by the set K. The specific commodities we consider are bottled water, food kits, medical kits, hygiene kits, energy kits, and tents. The edges in E represent any direct connection between a warehouse-DC pair, DC-DL pair, or any two DLs. To ensure tractability of the model, instead of determining the routes on the complete graph defined by the DCs and DLs, we make use of a pre-determined subset of routes, denoted by R. Each route in R starts from a DC $j \in J$, visits a set R_j of DLs, and returns to DC j.

The nonanticipative first-stage decision variables of the model consist of whether a warehouse $i \in I$ and DC $j \in J$ is open, denoted by binary variables y_i^1 and y_j^2, respectively; and continuous variables x_{ik}, which represent the amount of commodity $k \in K$ pre-positioned in warehouse $i \in I$. Opening a warehouse and DC incur a fixed cost of f_i^1 and f_j^2, respectively. Pre-positioning a unit of commodity $k \in K$ in warehouse $i \in I$ costs p_{ik} currency units. Facility opening and item pre-positioning costs are subject to a pre-disaster budget of B_1. Each unit of commodity $k \in K$ occupies a volume of β_k. The total storage and consolidation volume in a warehouse and DC cannot exceed the capacities of c_i^1 and c_j^2, respectively.

Unlike a vast majority of the studies in the inventory pre-positioning literature, we do not model uncertainty by means of discrete scenarios. The uncertainty on demand and road/facility damage is modeled in terms of continuous probability distributions, which are derived from the estimated *vulnerabilities* of DLs (v_d), facilities (v_i and v_j), and road segments (v_{ij}). Let ξ denote the set of (infinitely many) possible realizations of random network damage and demand, and let $\tilde{\xi}$ be a specific realization of of ξ. To model road vulnerability, we let $w^2_{ij}(\tilde{\xi})$ denote whether the road between $i \in I \cup J$ and $j \in J \cup D$ is operative under realization $\tilde{\xi} \in \xi$. With probability v_{ij}, the road is completely damaged, that is, $w^2_{ij}(\tilde{\xi}) = 0$. Assuming $\tilde{t}^1_{ij}$ (or $\tilde{t}^2_{jd}$) denotes the travel time on the road when there is no damage, we inflate this by a factor $(1 + u)$, where u is a uniformly distributed random number between 0 and v_{ij} to obtain $t^1_{ij}(\tilde{\xi})$ (or $t^2_{jd}(\tilde{\xi})$), which denotes the random travel time on the road. A DC $j \in J$ is assumed to be completely damaged with a probability of v_j. For demand amount of DL $d \in D$, we inflate the base demand $\tilde{\delta}_{dk}$ by a factor of $(1 + u)$ in a similar way to obtain the random demand $\delta_{dk}(\tilde{\xi})$.

The second-stage (recourse) decisions of the model relate to outsourcing, relief transportation, and repair. The amount of commodity $k \in K$ sent from warehouse $i \in I$ to DC $j \in J$ under $\tilde{\xi} \in \xi$ is denoted by $z_{ijk}(\tilde{\xi})$. For ease of coordination among facilities, we enforce a given commodity $k \in K$ to be delivered to demand point $d \in D$ from a single DC. For this end, the binary variable $s_{dkr}(\tilde{\xi})$ checks the DL is served by route $r \in R$. Binary variables $l_{ij}(\tilde{\xi})$ and $u_r(\tilde{\xi})$ reflect whether there is a shipment from warehouse $i \in I$ to DC $j \in J$ and whether route $r \in R$ is used under realization $\tilde{\xi} \in \xi$, respectively. The amount of commodity $k \in K$ outsourced in warehouse $i \in I$ under realization $\tilde{\xi} \in \xi$ is represented by $q_{ik}(\tilde{\xi})$. Binary variables $\gamma^1_{ij}(\tilde{\xi})$ and $\gamma^2_{jd}(\tilde{\xi})$ keep track of whether the road is repaired under realization $\tilde{\xi} \in \xi$. Lastly, $\alpha^2_{dk}(\tilde{\xi})$ represent the arrival time of commodity $k \in K$ at DL $d \in D$ under realization $\tilde{\xi} \in \xi$.

Repairing a road segment between warehouse $i \in I$ and DC $j \in J$ incurs a fixed cost of r^1_{ij}. A similar cost of r^2_{jd} applies for $j \in J \cup D$ and DL $d \in D$. The cost of using edge $(i, j \in E)$ is d^1_{ij} per unit volume of item, and the fixed cost of using route $r \in R$ is d^2_r. Outsourcing one unit of $k \in K$ in warehouse $i \in I$ costs o_{ik}. The total outsourcing, relief transportation, and repair cost is subject to a post-disaster budget of B_2. η_j is the predetermined dispatch time from DC $j \in J$, and the auxiliary variable g_{jdr} controls whether route $r \in R$ visits DC $j \in J$ and DL $d \in D$.

Given the index sets, parameters, and decision variables, the problem can be modeled as the following two-stage mixed integer stochastic program:

$$min \quad E_{\xi|\mathbf{x},\mathbf{y}}\left[f(\xi)\right] \tag{1}$$

$$\sum_{i \in I} f^1_i y^1_i + \sum_{j \in J} f^2_j y^2_j + \sum_{i \in I} \sum_{k \in K} p_k x_{ik} \leq B_1 \tag{2}$$

$$\sum_{k \in K} \beta_k x_{ik} \leq c^1_i y^1_i \qquad \forall i \in I \tag{3}$$

$$\mathbf{y} \in \{0, 1\}, \quad \mathbf{x} \geq 0, \tag{4}$$

where $f(\tilde{\xi})$ is the optimal solution to the following second-stage model:

$$min \quad \sum_{d \in D} \sum_{k \in K} \alpha^2_{dk}(\tilde{\xi})\, \delta_{dk}(\tilde{\xi}) \tag{5}$$

$$\sum_{j\in J}\sum_{k\in K} o_{ik}q_{ik}(\tilde{\xi}) + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} d^1_{ij}v_{ijk}(\tilde{\xi}) + \sum_{d\in D}\sum_{k\in K}\sum_{r\in R} d^2_r u_r(\tilde{\xi}) + \sum_{i\in I}\sum_{j\in J} r^1_{ij}\gamma^1_{ij}(\tilde{\xi}) + \sum_{j\in J}\sum_{d\in D} r^2_{jd}\gamma^2_{jd}(\tilde{\xi}) \leq B_2 \tag{6}$$

$$\sum_{k\in K}\beta_k q_{ik} \leq c^1_i y^1_i - \sum_{k\in K}\beta_k x_{ik} \qquad \forall i\in I \tag{7}$$

$$\sum_{j\in J} v_{ijk}(\tilde{\xi}) \leq x_{ik} + q_{ik}(\tilde{\xi}) \qquad \forall i\in I,\ k\in K \tag{8}$$

$$v_{ijk}(\tilde{\xi}) \leq M\, l_{ij}(\tilde{\xi}) \qquad \forall i\in I,\ j\in J,\ k\in K \tag{9}$$

$$l_{ij}(\tilde{\xi}) \leq w^2_{ij}(\tilde{\xi}) + \gamma^1_{ij}(\tilde{\xi}) \qquad \forall i\in I,\ j\in J \tag{10}$$

$$t^1_{ij}(\tilde{\xi})\, w^2_{ij}(\tilde{\xi})(1-\gamma^1_{ij}(\tilde{\xi})) + (\tilde{t}^1_{ij} + \rho_{ij}(\tilde{\xi}))\,\gamma^1_{ij}(\tilde{\xi}) \leq \eta_j + M\left(1 - l_{ij}\left(\tilde{\xi}\right)\right) \qquad \forall i\in I,\ j\in J \tag{11}$$

$$\sum_{i\in I}\sum_{k\in K}\beta_k v_{ijk}(\tilde{\xi}) \leq c^2_j y^2_j w^1_j(\tilde{\xi}) \qquad \forall j\in J \tag{12}$$

$$\sum_{d\in D}\sum_{r\in R_j} s_{dkr}(\tilde{\xi})\,\delta_{dk}(\tilde{\xi}) \leq \sum_{i\in I} v_{ijk}(\tilde{\xi}) \qquad \forall j\in J,\ k\in K \tag{13}$$

$$s_{dkr}(\tilde{\xi}) \leq u_r(\tilde{\xi})\, g_{dr} \qquad \forall d\in D,\ k\in K,\ r\in R \tag{14}$$

$$\sum_{r\in R} s_{dkr}(\tilde{\xi}) = 1 \qquad \forall d\in D,\ k\in K \tag{15}$$

$$u_r(\tilde{\xi}) \leq w^2_{ij}(\tilde{\xi}) + \gamma^2_{ij}(\tilde{\xi}) \qquad \forall r\in R,\ (i,j)\in r \tag{16}$$

$$\theta^2_{dr}(\tilde{\xi}) \geq \rho^2_{pred(d,r),d}(\tilde{\xi})\,\gamma^2_{pred(d,r),d}(\tilde{\xi}) + \tilde{t}^2_{pred(d,r),d} \qquad \forall d\in D,\ r\in R \tag{17}$$

$$\theta^2_{dr}(\tilde{\xi}) \geq \theta^2_{pred(d,r),r}(\tilde{\xi}) + \gamma^2_{pred(d,r),d}(\tilde{\xi})\,\tilde{t}^2_{pred(d,r),d} + \left(1 - \gamma^2_{pred(d,r),d}(\tilde{\xi})\right) t^2_{pred(d,r),d}(\tilde{\xi}) \qquad \forall d\in D,\ r\in R \tag{18}$$

$$\alpha^2_{dk}(\tilde{\xi}) \geq \eta_{j_r}\theta^2_{dr}(\tilde{\xi}) - M\left(1 - s_{dkr}(\tilde{\xi})\right) \qquad \forall d\in D,\ k\in K,\ r\in R \tag{19}$$

$$\mathbf{l}, \mathbf{u}, \gamma, \mathbf{s} \in \{0,1\} \tag{20}$$

$$\mathbf{q}, \alpha, \theta \geq 0, \tag{21}$$

where j_r corresponds to the origin DC of route $r \in R$ and $pred(d, r)$ denotes the predecessor of $d \in DL$ on route $r \in R$.

Since the first-stage decisions have no direct effect on the objective function, objective function (1) solely consists of the expectation of the second-stage objective value. Constraint (2) limits the first-stage costs by the budget, whereas constraints (3) ensure that to pre-position items in a warehouse, the warehouse must be open and its capacity cannot be exceeded. Constraints (4) restrict the facility opening variables as binary and pre-positioning variables as continuous.

The objective function given in (5) is the *efficacy-based* objective, which aims to minimize the total expected demand-weighted arrival times over all demand nodes and commodities. Constraint (6) is the budget constraint on the post-disaster operations of outsourcing, relief transportation, and road repair. Constraints (7) prohibit outsourcing to a warehouse where the capacity will be exceeded. Constraints (8) limit the outgoing deliveries from each warehouse by the total amount pre-positioned and outsourced. Constraints (9) ensure that deliveries can be made out of a warehouse only if the fixed cost can be incurred, whereas Constraints (10) prevent the traversal of a road segment between a warehouse and a DC unless either the road is unaffected by the disaster or repaired. Using Constraints (11) guarantee that all deliveries arrive at the DC before dispatch time. If the road is not completely damaged and not repaired, travel time is $t^1_{ij}(\tilde{\xi})$, whereas in case of a repair, the travel time is $\tilde{t}^1_{ij}$.

Constraints (12) prohibit any deliveries into a DC either if it is (i) completely damaged by the disaster or (ii) not located in the pre-disaster stage. The balance of flow into and out of a DC is ensured by Constraints (13), where the total demand satisfied by a given DC by routes starting from it cannot exceed the incoming deliveries from warehouses. With Constraints (14), the demand of a DL can be satisfied by a given route only if the route is selected and visits the DL. Assignment of a single route (DC) to a given DL for a given commodity is ensured by Constraints (15), whereas Constraints (16) prevent the use of a route unless each of the road segments of the route is either undamaged or repaired. Constraints (17) and (18) define the arrival time of a route at a given node. If a repair is ongoing when the relief delivery arrives at the predecessor d' of DL d, Constraints (17) define the arrival time as the ending time of repair and travel time of the undamaged segment. Otherwise, Constraints (18) handle the cases where (i) an ongoing repair has been finished before the arrival and (ii) the road is partially damaged and no repair has been carried out. Constraints (19) determine the actual arrival time of the commodities at a DL by making use of the assignment variable, whereas Constraints (20) and (21) impose binary and sign restrictions on the second-stage decision variables.

To assess the trade-off among different objectives on the performance of the decisions, we make use of three different objective functions. The objective given by (5) forms the *efficacy-based* objective function. For an *equity-based* approach, we minimize the expectation over the maximum expected demand-weighted arrival times, as opposed to the total. For this end, we replace (5) by:

$$min \quad \mu(\tilde{\xi}) \tag{22}$$

$$\mu(\tilde{\xi}) \geq \sum_{k \in K} \alpha^2_{dk}(\tilde{\xi})\, \delta_{dk}(\tilde{\xi}) \qquad \forall d \in D, \tag{23}$$

and solve the two-stage stochastic program defined by (1)-(4), (6)-(21), and (22)-(23).

As a third objective function alternative, we take a *robustness-based* approach and aim to minimize the maximum expected demand-weighted arrival time over all demand nodes and all possible realizations. To do so, we replace the objective function (1) of the first-stage model by:

$$min\, max_{\xi|\mathbf{x},\mathbf{y}}\, f(\xi), \tag{24}$$

and solve the model defined by (2)-(4), (6)-(21), and (22)-(24).

For each of the three alternative models, we include the remaining two objective functions in each model with a small coefficient to avoid alternative solutions with worse values of the remaining objectives.

3.3 A Heuristic Approach Based on Sample Average Approximation

The main challenge with solving the two-stage stochastic program defined by (1)-(21) arises from having to calculate the expectation in the objective. Since the random variables representing travel and repair time ($t^1_{ij}(\tilde{\xi})$, $t^2_{jd}(\tilde{\xi})$, and $\rho_{ij}(\tilde{\xi})$) are continuous, the expectation is over infinitely many potential outcomes. Furthermore, even without the existence of these, the number of potential realizations is still excessive. For an instance with $|E|$ road segments, the random parameter $w^2_{ij}(\tilde{\xi})$ may take $2^{|E|}$ possible values. Even for small-sized instances, this leads to substantial computational burden.

To overcome the computational challenges resulting from calculating the objective function, we use a *sample average approximation* approach. The main idea behind SAA is that by sampling over a number of potential discrete scenarios, the true value of objective function (1) can be approximately calculated. The use of discrete scenarios also allows the formulation of the two-stage stochastic programming model as a single deterministic mixed integer program, which can be solved using existing algorithms and commercial/open-source solvers. Furthermore, as shown by Kleywegt et al. (2001), the SAA method asymptotically converges to the optimal value of the original objective function as the number of sampled scenarios increases.

The approximation scheme works by generating a number of samples, each with a small amount of scenarios. The resulting integer program is solved for each sample to obtain the first-stage decisions. These decisions are evaluated using a larger sample of scenarios, and the best decision set is selected among the samples. Selecting a large number of samples and/or scenarios increases the accuracy of the objective function approximation, whereas it also leads to a higher computational burden. Hence, the algorithm parameters (number of samples and scenarios to determine the first-stage decisions, and the number of scenarios for evaluation) should be determined so as to resolve this trade-off as effectively as possible. These parameters are determined using preliminary experiments in Section 4.

The SAA approach can be carried out in a number of different ways. Mostly following the scheme applied by Chang et al. (2007), the steps of the SAA approach specific to our problem are as follows.

Step 1. Using the vulnerability values (which serve as probabilities), generate M independent samples of the random parameters w^1_j, w^2_{ij}, t^1_{ij}, t^2_{jd}, ρ_{ij}, and δ_{dk}, each of size N. For example, for w^1_j, this implies generating a set of vectors $\left\{\mathbf{w}^1_{m,1}(\psi), \mathbf{w}^1_{m,2}(\psi), \dots, \mathbf{w}^1_{m,N}(\psi)\right\}$ for $m \in \{1, 2, \dots, M\}$, and $\mathbf{w^1} = \left\{w^1_j\left(\tilde{\xi}\right), \forall j \in J, \tilde{\xi} \in \xi\right\}$.

For each of the scenarios in each of the M samples, replace the random parameters by their generated values. For each sample, solve the model with the objective:

$$\begin{aligned} min \quad & \frac{1}{N}\sum_{n=1}^{n}\sum_{d\in D}\sum_{k\in K}\sum_{r\in R}\alpha^2_{dkr}(\tilde{\xi})\,\delta_{dk}(\tilde{\xi}) \\ s.t. \quad & (2)-(21). \end{aligned}$$

Let $(\tilde{X},\tilde{Y})^m$ be the vectors of first-stage decisions in sample m, where $m = 1, 2, \ldots, M$. Here, $\tilde{X} = \{x_{ik}, \forall i \in I, k \in K\}$ and $\tilde{Y} = \{y_i^1, \forall i \in I\} \cup \{y_j^2, \forall j \in J\}$. Furthermore, let $\hat{z}_m$ be the optimal objective value of the mixed integer program corresponding to the i^{th} sample.

Step 2. Compute the average and variance of the optimal values obtained by the samples (denoted by $\bar{z}$ and $\sigma^2_{\bar{z}}$, respectively) as follows:

$$\bar{z} = \frac{1}{M}\sum_{m=1}^{M}\hat{z}_m$$

$$\sigma^2_{\bar{z}} = \frac{\sum_{m=1}^{M}(\hat{z}_m - \bar{z})^2}{M\,(M-1)}.$$

Here, $\bar{z}$ constitutes a lower bound on the optimal objective value of the original model, and $\sigma^2_{\bar{z}}$ estimates the variance of $\bar{z}$.

Step 3. For each sample $m = 1, 2, \ldots, M$, generate $N' >> N$ independent scenarios, following the procedure in Step 1. Use $(\tilde{X},\tilde{Y})^m$ as parameters to solve the reduced model:

$$\bar{z}\,(\tilde{X},\tilde{Y})^m = min \quad \frac{1}{N'}\sum_{n=1}^{N'}\sum_{d\in D}\sum_{k\in K}\sum_{r\in R}\alpha^2_{dkr}(\xi)\,\delta_{dk}(\xi)$$

$$s.t. \quad (2) - (21).$$

Let $m' = argmin_m \left\{\bar{z}\,(\tilde{X},\tilde{Y})^m\right\}$ and $\bar{z}_s\,(\tilde{X},\tilde{Y})^{m'}$ be the optimal solution of the reduced model with $(\tilde{X},\tilde{Y})^{m'}$ under the s^{th} scenario, where $s = 1, 2, \ldots, N'$. Compute the estimated variance:

$$\hat{\sigma}^2_{\bar{z}}(\tilde{X},\tilde{Y})^{m'} = \frac{\sum_{s=1}^{N'}\left(\bar{z}_s\,(\tilde{X},\tilde{Y})^{m'} - \bar{z}(\tilde{X},\tilde{Y})^{m'}\right)^2}{N'\,(N'-1)}.$$

Step 4. Terminate with $(\tilde{X},\tilde{Y})^{m'}$ as the heuristic solution and construct a $1-\alpha$-confidence interval for the optimal value of the original model as:

$$\left[\bar{z}(\tilde{X},\tilde{Y})^{m'} - z_{\frac{\alpha}{2}}\,\frac{\hat{\sigma}^2_{\bar{z}}(\tilde{X},\tilde{Y})^{m'}}{\sqrt{N'}},\ \bar{z}(\tilde{X},\tilde{Y})^{m'} + z_{\frac{\alpha}{2}}\,\frac{\hat{\sigma}^2_{\bar{z}}(\tilde{X},\tilde{Y})^{m'}}{\sqrt{N'}}\right],$$

where the normal approximation is due to the large size of N'.

To observe the precision of the estimation, we use the ratio of the half-width of this interval to the estimated mean of $\bar{z}(\tilde{X},\tilde{Y})^{m'}$.

3.4 Valid Inequalities and Objective Value Bounds

The SAA procedure described in Section 3.3 is a generic procedure, and hence does not take advantage of any structural properties of the problem. To enhance its computational efficiency, we introduce a number of valid inequalities and objective value bounds in this section. Part of these have been derived from their counterparts in the humanitarian network design and location-routing literature, whereas the remainder have been specifically formulated for this problem.

The first valid inequality, which is derived directly from the structure of the optimal solution, asserts that the repair of a road segment between a warehouse and DC may only be viable when: (1) that road segment is used for a shipment between the two facilities, (2) both the warehouse and DC at each end of the segment are open, (3) the corresponding DC should be operational, and (4) the road segment is (at least partly) damaged by the disaster.

In mathematical terms, this implies that $\gamma^1_{ij}(\tilde{\xi})$ may take a value of 1 only when $l_{ij}(\tilde{\xi} = y^1_i = y^2_j = w^1_j(\tilde{\xi}) = 1$ and $w^2_{ij}(\tilde{\xi}) = 0$. This is defined by the following proposition.

Proposition 1 *For a link* (i, j) *where* $i \in I$ *and* $j \in J$*, the following inequality is valid:*

$$\gamma^1_{ij}(\tilde{\xi}) \leq \frac{l_{ij}(\tilde{\xi}) + y^1_i + y^2_j + w^1_j(\tilde{\xi}) + (1 - w^2_{ij}(\tilde{\xi}))}{5} \quad \forall i \in I,\ j \in J, \tilde{\xi} \in \xi. \tag{25}$$

Proof. Since $\gamma_{ij}(\tilde{\xi})$ have positive coefficients in Constraint (6); by combining Constraints (10) and (11), we conclude that $\gamma^1_{ij}(\tilde{\xi}) = 1$ only when $l_{ij}(\tilde{\xi}) = 1$, and hence $\gamma^1_{ij}(\tilde{\xi}) \leq l_{ij}(\tilde{\xi})$ is valid. By Constraints (10), when $l_{ij} = 1$ and $w^2_{ij} = 1$, $\gamma^1_{ij}(\tilde{\xi}) = 0$ is always feasible. Thus, $\gamma^1_{ij}(\tilde{\xi}) \leq 1 - w^2_{ij}(\tilde{\xi})$ is also valid.

From Constraints (9), (10), and (11), we deduce that $l_{ij}(\tilde{\xi}) = 1$ only when $v_{ijk}(\tilde{\xi}) > 0$. From Constraints (7) and (8), $v_{ijk}(\tilde{\xi}) > 0$ is possible only when $y^1_i = 1$. Thus, $\gamma^1_{ij}(\tilde{\xi}) \leq y^1_i$ is valid. From Constraints (12), we have $v_{ijk}(\tilde{\xi}) > 0$ only when $y^2_j = 1$ and $w^1_j(\tilde{\xi}) = 1$. Thus, $\gamma^1_{ij}(\tilde{\xi}) \leq y^2_j$ and $\gamma^1_{ij}(\tilde{\xi}) \leq w^1_j(\tilde{\xi})$ are also valid.

Adding all the five valid identities and dividing both sides of the resulting inequality by 5 obtains the inequality in the proposition. □

It should be noted that taking the floor function of the right-hand side would lead to an even stronger valid inequality, but would also lead to a nonlinear model.

The second set of valid inequalities is analogous to the first, but focuses on the routes visiting the DLs. Here, in the optimal solution, a road segment between a DC/DL and another DL can be repaired only when (1) the route which includes the road segment is used for relief distribution, (2) the corresponding DC is open and unaffected by the disaster, and (3) the road segment is (at least partly) damaged. The formal definition of this relationship is given by the following proposition.

Proposition 2 *For an edge* $(i, j) \in r$*,* $r \in R$*, the following inequality is valid:*

$$\gamma^2_{ij}(\tilde{\xi}) \leq \frac{u_r(\tilde{\xi}) + y^2_{j_r} + w^1_{j_r}(\tilde{\xi}) + (1 - w^2_{ij}(\tilde{\xi}))}{4} \quad \forall (i, j) \in r,\ r \in R, \tilde{\xi} \in \xi, \tag{26}$$

where j_r is the index of the DC at the start of route $r \in R$.

Proof. $\gamma^2_{ij}(\tilde{\xi})$ have positive coefficients in Constraint (6). Using this with Constraints (16), $\gamma^2_{ij}(\tilde{\xi}) = 1$ only when $u_r(\tilde{\xi}) = 1$. Thus $\gamma^2_{ij}(\tilde{\xi}) \le u_r(\tilde{\xi})$ is valid. Furthermore, $w^2_{ij}(\tilde{\xi}) = 1$ is sufficient for $u_r(\tilde{\xi}) = 1$, thus $\gamma^2_{ij}(\tilde{\xi}) \le 1 - w^2_{ij}(\tilde{\xi})$ is also valid.

From Constraints (14), we also observe that $u_r(\tilde{\xi}) = 1$ only when at least one of the corresponding $s_{dkr} = 1$. Using Constraints (12) and (13), this is only possible when both y^2_j and $w^1_j(\tilde{\xi})$ corresponding to this route equal 1. Hence, $\gamma^2_{ij}(\tilde{\xi}) \le y^2_{j_r}$ and $\gamma^2_{ij}(\tilde{\xi}) \le w^1_{j_r}(\tilde{\xi})$ are both valid.

When these four identities are summed up and the total is divided by 4, the desired inequality is obtained. □

The third and fourth set of valid inequalities are extended from Toyoğlu et al. (2012) for a different version of the LRP. The main idea is that if there is no outflow (or inflow) from a node, then no vehicle should be dispatched from (or arrive at) it.

For the case of DCs, if the total amount of relief shipment out of that DC is zero, then all binary variables representing deliveries from each warehouse to this DC should be zero as well. In other words, if $v_{ijk}(\tilde{\xi}) = 0$ for some commodity $k \in K$, then $l_{ij}(\tilde{\xi}) = 0$ should hold for this $i \in I$ and $j \in J$ pair.

Proposition 3 *The following set of inequalities are valid for a given warehouse $i \in I$, a DC $j \in J$ and for each scenario:*

$$l_{ij}(\tilde{\xi}) \le \sum_{k \in K} v_{ijk}(\tilde{\xi}) \quad \forall i \in I,\ j \in J,\ \tilde{\xi} \in \xi \tag{27}$$

For the DLs, a further extension is made; we stipulate that for a shipment of a commodity to be made into a DL, the DL should have demand of that commodity in that scenario. Thus, for a given DL $d \in D$ and commodity $k \in K$ on a route $r \in R$, $s_{dkr}(\tilde{\xi}) = 1$ is possible only when $\delta_{dk}(\tilde{\xi}) > 0$ and $g_{dr} > 0$ both hold.

Proposition 4 *Given a DL $d \in D$, a commodity $k \in K$, and route $r \in R$ that includes d, the following set of inequalities are valid in each scenario:*

$$s_{dkr}(\tilde{\xi}) \le \delta_{dk}(\tilde{\xi}) g_{dr} \quad \forall d \in D,\ k \in K,\ r \in R,\ \tilde{\xi} \in \xi. \tag{28}$$

The following set of valid inequalities are commonly used in the LRP literature (e.g., Karaoğlan et al., 2012), and are directly used in our approach. Here, for each DL, at least one of the DCs at the origin of the routes serving this specific DL should be open.

Proposition 5 *The following set of inequalities are valid for each DL in each scenario:*

$$\sum_{j \in J_d} y_j^2 \geq 1 \quad \forall d \in D, \tilde{\xi} \in \xi, \tag{29}$$

where J_d refers to the set of DCs connected to DL $d \in D$ in the pre-disaster network.

For an open DC, a useful set of valid inequalities, derived from the structure of the optimal solution, provide lower bounds for the total number of routes starting from this DC. Here, a valid lower bound is the ratio of the total shipment into the DC (hence its capacity) to the maximum possible total demand faced by the DLs that are on the routes emanating from the DC.

Proposition 6 *The following inequalities are valid for each DC $j \in J$ and commodity $k \in K$ in each scenario:*

$$\sum_{r \in R_j} u_r(\tilde{\xi}) \geq \frac{\sum_{i \in I} v_{ijk}(\tilde{\xi})}{\max_{r \in R_j} \left\{ \sum_{d \in D_r} \delta_{dk}(\tilde{\xi}) \right\}} - M(1 - y_j^2) \quad \forall j \in J,\ k \in K,\ \tilde{\xi} \in \xi. \tag{30}$$

Proof. *(Sketch)* If DC $j \in J$ is not open, then the constraint is obviously redundant. Otherwise, it is easy to show that in an optimal solution, all shipments of commodity $k \in K$ shipped into $j \in J$ will be transported to the DLs. The maximum possible number of outgoing shipments is bounded below by the ratio of the incoming amount to the maximum possible demand faced by this DC. The latter is bounded above by the maximum total demand faced by any of the predetermined routes emanating from j. Since the denominator attains its maximum value in this case, the whole ratio corresponds to a lower bound on the value of the left-hand side. □

Following similar ideas from the LRP literature (e.g., Perboli et al., 2011; Karaoğlan et al., 2012; Toyoğlu et al., 2012), the last set of valid inequalities can be used as a lower bound for the number of open DCs, where the number is bounded below by the total demand throughout the whole system divided by the total possibly available capacity. More formally, the sum of y_j^2 over all DCs $j \in J$ is no less than the ratio of total demand volume ($\sum_{d \in D} \sum_{k \in K} \beta_k \delta_{dk}(\tilde{\xi})$) to the maximum total possible capacity ($\max_{j \in J}\{c_j^2\}$).

Proposition 7 *The following inequalities are valid in each scenario:*

$$\sum_{j \in J} y_j^2 \geq \left\lceil \frac{\sum_{d \in D} \sum_{k \in K} \beta_k \delta_{dk}(\tilde{\xi})}{\max_{j \in J}\{c_j^2\}} \right\rceil \quad \forall \tilde{\xi} \in \xi. \tag{31}$$

The last set of inequalities specifically make use of the worst-case arrival times of the optimal solutions under each scenario and provide an upper bound on the objective function value, which leads to substantial computational time savings during the solution process. In any given scenario, each delivery vehicle leaves the DCs at a predetermined dispatch time. Furthermore, since the network structure is known for each scenario, the arrival times of each route at each demand node (if an arrival is feasible) can be immediately calculated. The worst-case arrival time of a commodity at a DL is no worse than the maximum arrival times of the routes over all DCs.

From a mathematical standpoint, if we know that a route $r \in R$ is chosen and what scenario $\tilde{\xi} \in \xi$ has occurred, we can immediately determine the time $\bar{\theta}^2_{dr}(\tilde{\xi})$ that elapses from departing from DC j_r until reaching demand node $d \in D$ under that scenario using Constraints (17) and (18). Since these are easy to calculate, the upper bounds are also very easy to obtain.

Proposition 8 *The following inequalities provide an upper bound on the arrival time at each DL $d \in D$ for commodity $k \in K$ in each scenario:*

$$\alpha^2_{dk}(\tilde{\xi}) \le \max_{j\in J}\left\{\eta_j + \max_{r\in R}\bar{\theta}^2_{rd}(\tilde{\xi})\right\} \quad \forall d \in D,\ k \in K,\ \tilde{\xi} \in \xi. \tag{32}$$

4 A Case Study on a Potential Earthquake Scenario in Istanbul, Turkey

To evaluate the effectiveness of repair decisions in the inventory pre-positioning and relief distribution, as well as to assess the performance of our proposed SAA approach, we apply the proposed models and solution approaches in Section 4 to a potential earthquake scenario in Istanbul, Turkey. With a population of nearly 15 million and generating more than 40% of the gross national product of Turkey, Istanbul is one of the most densely populated cities that lie near highly active seismic zones. According to the Istanbul Seismic Risk Mitigation and Emergency Project (ISMEP, 2015), the probability of an earthquake with a Richter scale of at least 7.0 within the next 10 years exceeds 20%, whereas the same probability is more than 62% for the next 30 years. It is estimated that more than 70,000 may die and 120,000 may be severely injured after a probable 7.5-scale earthquake, with an economic loss of more than 50 billion USD, which altogether underline the need for effective preparedness.

4.1 Instance Settings

Our instances are based on the potential damage assessments of Istanbul under the current network conditions and demographics of the city. In this section, we summarize how various parameters are determined. The values, probability distributions, or sources of these are also given in Table 3.

Demand points: Our instances are based on 37 of the 39 districts of Istanbul, each of which constitutes a demand point. Of the two districts not considered, Adalar is an archipelago and thus separated from the mainland, and Şile is only marginally affected by the earthquake due to its distance from the potential epicenter and low population.

Table 3: Parameter values for the case study

Set/Parameter	Description	Value, distribution, or source
$\|I\|$	Number of potential warehouses	25
$\|J\|$	Number of potential DCs	37
$\|D\|$	Number of DLs	37
$\|K\|$	Number of commodities	6
$\|R\|$	Number of predetermined routes	428
c_i^1, c_j^2	Facility capacities	Based on Aslan (2016)
f_1^i, f_2^j	Fixed costs	Based on Aslan (2016)
β_k, p_{ik}, o_{ik}	Commodity volumes and costs	Based on IFRC (2015)
B_1	Pre-disaster budget	TL 1 billion
B_2	Post-disaster budget	TL 750 million
$\bar{t}_{ij}^1$, $\bar{t}_{jd}^2$, d_{ij}^1, d_r^2	Pre-disaster travel times and costs	Based on Diva-GIS (2017) and speeds of 30-60 km/h
η_j	Dispatch time	Ranging from 20 to 60 minutes
$\delta_{dk}(\tilde{\xi})$	Demand amounts	Based on JICA (2002) and Turkish Statistical Institute (2013)
$w_j^1(\tilde{\xi})$	DC failure probabilities	Based on JICA (2002), ranging from 3% to 40%
$t_{ij}^1(\tilde{\xi})$, $t_{jd}^2((\tilde{\xi}))$	Post-disaster travel times	Based on Başkaya et al. (2017)
$w_{ij}^2(\tilde{\xi})$	Complete road blockage probabilities	Using Equation (33), ranging from 10% to 30%
r_{ij}^1, r_{jd}^2, $\rho_{ij}(\tilde{\xi})$	Repair times and costs	Based on Furuta et al. (2011)

Demand amounts: To determine the demand amounts, we make use of two reports: (i) by the JICA (Japan International Cooperation Agency, 2002), which provides the estimated percentage of population in heavily and moderately damaged buildings, as well as that of dead and severely injured people and (ii) the 2012 population census report (Turkish Statistical Institute, 2013), which provides the most up-to-date populations of the districts. Of the four main scenarios in the JICA report, we take weighted averages of the corresponding percentages of scenarios A (most likely) and C (most severe). We assume that every individual in a heavily or severely damaged building that survives the disaster without severe injuries will need water, energy kits, hygiene kits, and food bundles. Furthermore, it is assumed that every such family (with an average of four individuals) will require tents and medical kits. Randomness of demand is obtained by inflating these base amounts by a factor that depends on the district (facility) vulnerabilities.

Potential warehouse and DC locations: We set all 37 demand points as potential DC locations. A potential warehouse may be located in a district if the total weighted demand in that district exceeds 75% of the weighted average over all districts, which leads to 25 potential warehouse locations. For the determination of fixed costs and capacities of these facilities, interested reader is referred to Aslan (2016).

Road network: We assume a direct path between each potential warehouse-DC pair. Deliveries from distribution centers to demand points are assumed to be made through routes that visit multiple districts. Since the exact list of routes predetermined by the IMM is not available in ISMEP (2015) is not publicly available, we use a nearest neighbor based-approach to generate the routes. For each DC-DL pair, we run Algorithm 1 to generate the set of candidate routes that emanate from the given DC and that start with the given DL. We use $\chi \in \{2, 3, 4\}$ and $\phi = 40$ minutes. In the resulting instance, each DL is visited from at least six potential DCs, and a total of 428 routes are generated in this manner, each visiting a maximum of four DLs.

Algorithm 1 Route generation algorithm

```
Given a DC j, DL d, predetermined route size χ and a threshold time ϕ
size ← 1
if t_jd > ϕ then
    Discard route
else
    current ← d
    while size ≤ χ do
        Let d′ be the nearest neighbor of current not in the tour
        if t_current,d′ > ϕ then
            return Current tour
        else
            Add d′ to the end of the tour and set current ← d′
            size ← size + 1
        end if
        return Current tour
    end while
end if
```

With $|J|$ DCs and $|D|$ DLs, Algorithm 1 has a worst-case complexity of $O(|J||D|)$, since it is run for each DC-DL pair and for a constant maximum route size. This provides significant computational savings compared to considering all potential routes, which would be exponential in $|J|$.

The pairwise travel distances between districts are calculated based on the road shapefile obtained from Diva-GIS (2017) and the Network Analyst tool of ArcGIS 10.5. On a motorway and primary road, truck speeds are assumed as 60 km/h and 30 km/h, respectively. The resulting times are incurred when the road is undamaged or repaired. When a road segment is not completely damaged, its travel time is determined by inflating the base travel times by a vulnerability factor. Repair times are assumed five times as those of the original travel times. The road network and the locations of the district centers (DLs and potential facility locations) are given in Figure 2.

District vulnerabilities: Facility vulnerabilities are determined based on the district each of the facilities is located in, which is obtained from Japan International Cooperation Agency (2002) by taking a weighted average of the vulnerabilities corresponding to scenarios A and C. The resulting vulnerabilities, which range from 3% to 40% for the base case, are given in the map on Figure 3. These are used to determine the probabilities that each DC may be damaged, as well as inflation factors for the demand amounts.

Road vulnerabilities: Road vulnerabilities are incorporated in two ways: by means of complete road blockage or inflated travel times on each segment. Based on our consultations with experts from the Istanbul Metropolitan Municipality, incorporation of decreases in road capacity have not been explicitly considered.

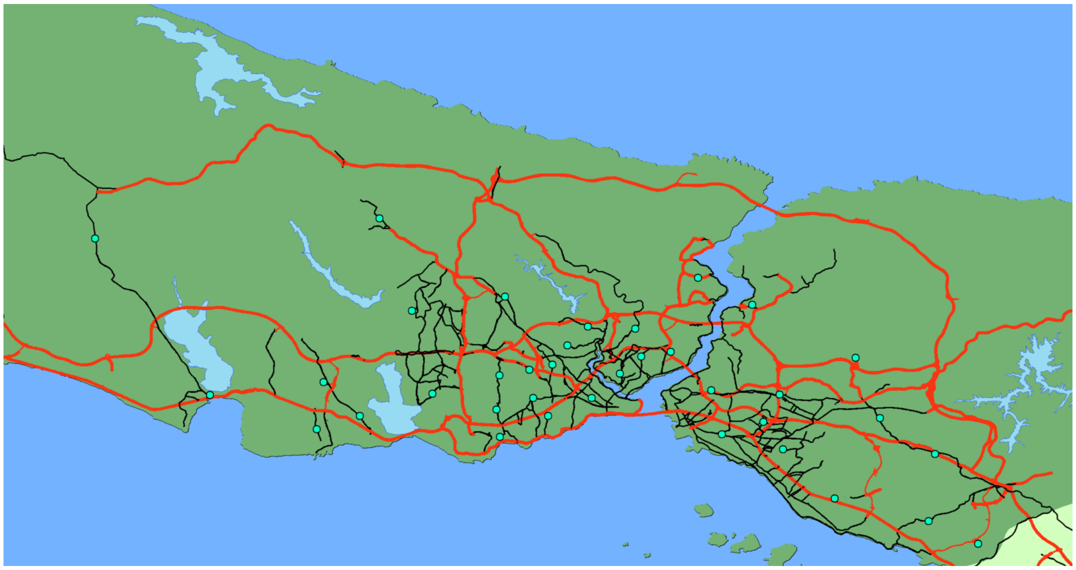

Figure 2: The road network and demand locations used in the case study

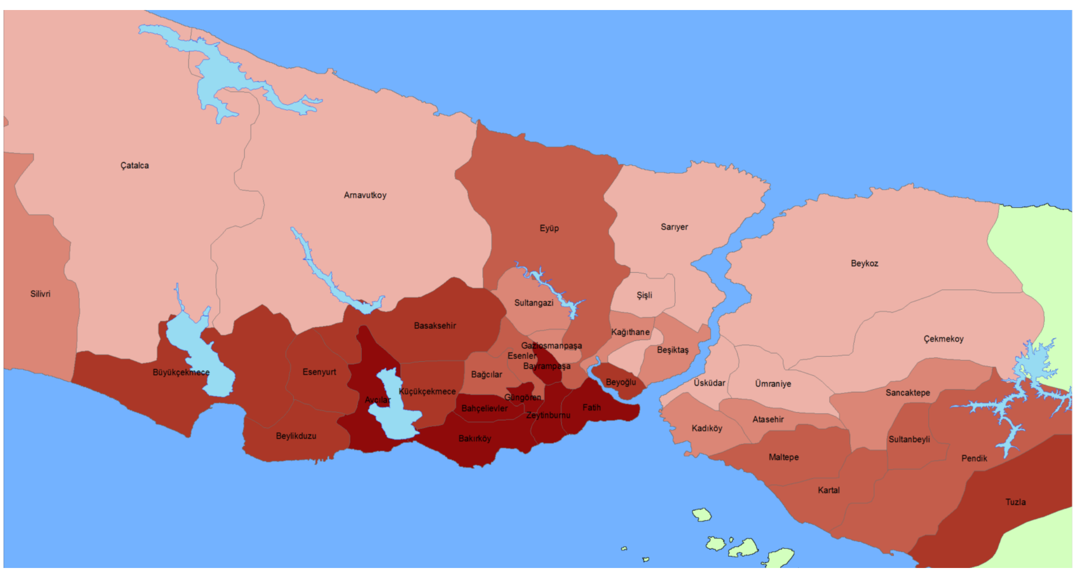

Figure 3: Normalized vulnerabilities of each district in the case study

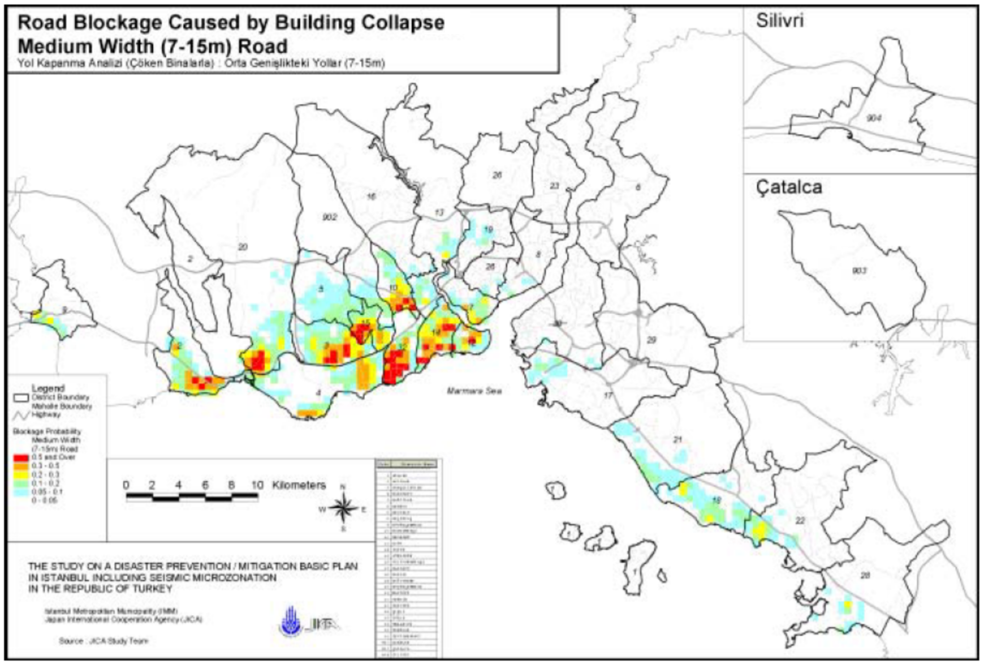

Figure 4: Level of road blockage for medium-width roads (Japan International Cooperation Agency, 2002)

We assume that when a road is not completely damaged, it can be traversed at an inflated travel time depending on its vulnerability. To determine the vulnerability levels, we use the two-step approach by Başkaya et al. (2017), where the vulnerablities of medium-sized roads from Japan International Cooperation Agency (2002) are used to calculate the inflation factors. First, we make use of the coloring scheme in Figure 4 to overlay this map with the road network in Figure 2. Then for each district pair, we calculate the vulnerability factor of the path by taking the geometric average of the vulnerability values corresponding to each color encountered on it (the factors are 75%, 40%, 25%, 15%, 7.5%, and 2.5% for red, orange, yellow, green, blue, and grey, respectively).

The probability p_{ij} that a road segment (i, j) is completely blocked (its vulnerability) is calculated based on Salman and Yücel (2015) as:

$$p_{ij} = 1 - \alpha \beta_{ij} \frac{e^{0.8\mu}}{(r_{ij} + 40)^2}, \tag{33}$$

where $\alpha = 2$, $\beta_{ij} \in \{0.65, 0.75, 0.85, 0.95\}$ based on the risk region of the centroid of the shortest path from i to j, $\mu = 7.4$, and r_{ij} is the distance between the epicenter of the earthquake and the centroid of the path. By this way, the probability of a complete damage varies from 10% to 30% in the base case.

Costs and budget: For the relief items, volumes and unit procurement costs are obtained from International Federation of Red Cross and Red Crescent Societies (2015) for pre-positioning. A factor of 25% is used to inflate these for outsourcing costs. Transportation costs are calculated based on full truckloads between warehouses and DCs, and less-than-truckloads from DCs to DLs. Details of these calculations are provided in Aslan (2016). Repair costs, which are borrowed from Furuta et al. (2011), depend on the risk region of the centroid of each path. Based on preliminary experiments and discussions with the IMM, the first- and second-stage budgets are set at TL 1 billion and TL 750 million, respectively.

For the remainder of this section, our experiments are performed on a Xeon Quad-Core Server with 32 GB RAM using ILOG CPLEX Solver version 12.6 with Concert technology.

4.2 Preliminary Experiments

Before we conduct the main experiments, we aim to assess the accuracy, precision, and timeliness of the SAA scheme, and evaluate the improvements resulting from the addition of valid inequalities and bounds by performing a set of preliminary computational experiments to determine the number of samples (M) and that of scenarios (N) in each sample of the SAA scheme throughout our main experiments. For this purpose, we apply the four-step approach in Section 3.3 to the base case by varying M as 36, 60, 90, 120, 180, and 240. In each case, N is varied as 10, 20, 50, and 100, and the time limit is 24 hours. We use different seeds to generate the scenarios for varying (M, N) pairs. However, we use the same set of scenarios within the same (M, N) pair to compare the cases without and with valid inequalities. In making these experiments, we would like to obtain a setting where (1) the optimal objective value is accurately estimated, i.e., objective value of the heuristic solution changes only marginally by perturbing the parameters; (2) the estimation is precise, for which we require the half-length of the confidence interval to be as narrow as possible; and (3) application of the proposed approach takes reasonable time considering the problem environment.

The results of the preliminary experiments on the efficacy-based baseline model are presented in Table 4 for varying values of N and M, with N' fixed at 5,000. We observe that when N exceeds 90, the estimated objective values are within 1% of one another, particularly at higher M levels of 50 or 100. The mean objective values stabilizing around 111 million with varying seeds is a promising indicator of the accuracy at these levels. With smaller values of the parameters, the mean objective values tend to be larger, thus we drop these settings from consideration.

The precision of the estimations tends to follow a similar pattern when parameters are varied. The 95% confidence interval half-width around the estimated optimal objective value is within almost 1% when $N \geq 120$ and $M \geq 50$. One observation here is that when N increases from 180 to 240, the improvements in accuracy become marginal. Given the higher CPU time requirements at higher N values, this leads us to remove $N = 240$ from consideration as well.

By analyzing the CPU times of these experiments, we are also able to assess the effectiveness of the valid inequalities introduced in Section 3.4. Table 4 shows that at higher N and M values, the original model without valid inequalities fails to find the optimal solutions for a number of samples. In contrast, the largest instances can be solved within 18 hours when the inequalities are included. Furthermore, for any given setting, the CPU time improvement

Table 4: Average objective values, 95% confidence interval half-width ratios, and CPU times for the preliminary experiments on the efficacy-based baseline model, dashes indicating time limit is exceeded ($\bar{z}$: average expected objective value over all replications, 95% CI HL / $\bar{z}$: ratio of the 95% confidence interval for the optimal objective value to the average over all replications, VI: valid inequalities)

N	M	$\bar{z}$	95% CI HL / $\bar{z}$	CPU time without VI (sec)	CPU time with VI (sec)
30	10	126,241,346	5.52%	833.04	406.73
	20	119,856,368	4.22%	1,724.53	822.19
	50	121,569,263	3.78%	4,262.28	1,801.76
	100	118,659,807	2,69%	9,005.53	3,932.11
60	10	116,778,589	3.20%	2,497.57	1,025.40
	20	108,266,456	2.99%	4,882.24	2,104.36
	50	110,571,891	2.58%	7,938.44	3,634.87
	100	114,931,005	2.32%	16,219.84	7,793.45
90	10	119,983,754	3.01%	5,581.29	2,446.72
	20	115,509,212	2.76%	11,830.54	4,914.30
	50	111,831,098	2.25%	27,383.22	11,046.19
	100	112,149,216	1.98%	62,567.80	24,352.88
120	10	118,930,352	2.96%	7,464.93	3,352.16
	20	112,356,264	2.48%	18,732.69	7,518.48
	50	111,353,592	1.28%	46,525.74	19,284.32
	100	110,924,784	1.19%	—	34,874.72
180	10	113,849,232	2.46%	13,930.20	5,854.43
	20	111,932,714	1.79%	28,294.09	12,482.03
	50	111,126,835	1.06%	81,483.20	28,702.41
	100	111,273,021	1.02%	—	46,295.92
240	10	112,742,299	2.23%	27,956.42	9,252.49
	20	111,586,660	1.59%	59,294.11	16,613.92
	50	111,279,221	1.03%	—	37,672.13
	100	111,145,035	0.99%	—	64,929.10

brought about by the valid inequalities is always more than 50% and reaches 66% in a number of cases. Consequently, we retain the valid inequalities throughout the remainder of our experiments.

Among the remaining (M, N) pairs under consideration, we conclude with $M = 50$ and $N = 180$. This is mainly because instances with this setting can be solved within 8 hours, which is quite acceptable as the problem is faced in the preparedness stage of the disaster. Another reason is that when N is fixed, increasing M from 50 to 100 does not have considerable effect in increasing the accuracy or precision significantly; when $N = 180$, where is an improvement of 0.05% in precision, but this is at the expense of another 5 hours of CPU time.

It should be noted here that for benchmark models where road vulnerability is modeled in different ways, road repair is ignored, and an equity-based objective is used, the accuracy, precision, and computational times are no worse than those presented in Table 4.

4.3 Computational Results

For the assessment of solving the model under different objectives, assumptions, and parameter settings, we make use of a number of optimality gaps. Let $z^o_{i|j}$ denote the i^{th} objective value of the SAA solution obtained for the minimization of objective j ($i, j = 1, 2, 3$ correspond to the objectives related to efficacy, equity, and robustness, respectively). Thus, $z^o_{i|i}$ is the best heuristic solution that can be achieved under objective i. Based on these, we define the *objective gap* $OG_{i|j}$ as $(z^o_{i|j} - z^o_{i|i})/z^o_{i|i}$, which measures the loss in the objective function i when a model based on objective j is implemented,

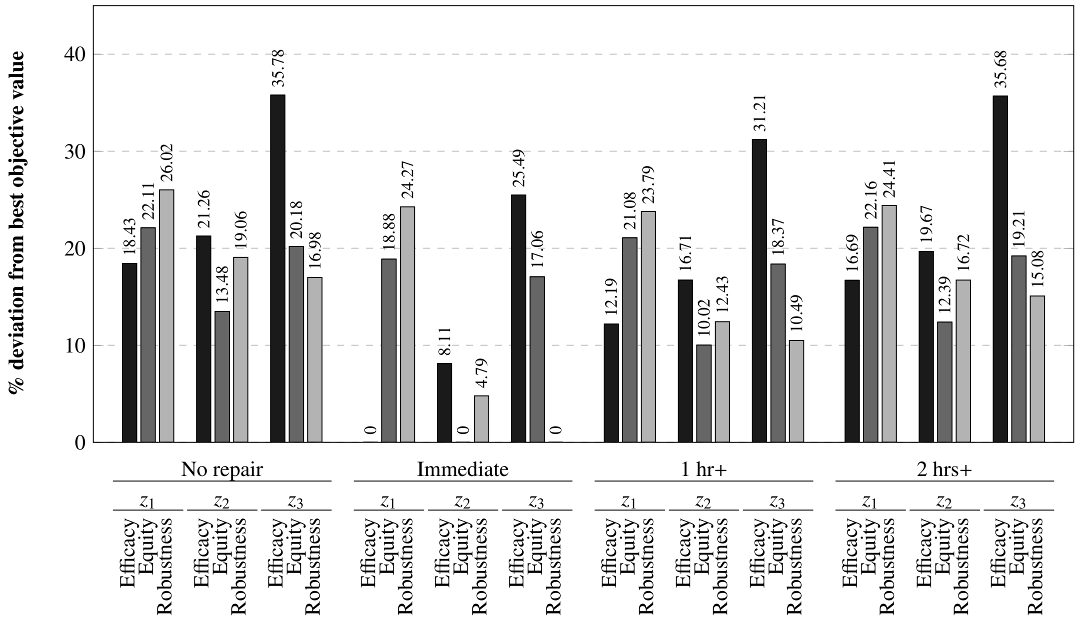

Figure 5: Percent deviations of each model (z_1: efficacy-based, z_2: equity-based, z_3: robustness-based) under each repair assumption (no repair, immediately available repair, repair available after 1 hour, and repair available after 2 hours) from the best efficacy, equity, and robustness objective values

when all other settings are identical. Similarly, let $z^a_{i|j}$ and $z^p_{i|j}$ represent the objective value under assumption a and parameter settings p respectively (with all else identical). Then, the *assumption gap* $AG_{i|j}$ and *parameter gap* $PG_{i|j}$ are given by $(z^a_{i|j} - z^a_{i|i})/z^a_{i|i}$ and $(z^p_{i|j} - z^p_{i|i})/z^p_{i|i}$, respectively.

We present our computational results in four parts. These parts involve the analysis of inclusion of repair in the post-disaster stage (§4.3.1), objective function selection (§4.3.2), road vulnerability assumptions (§4.3.3), and sensitivity to problem parameters (§4.3.4).

4.3.1 Results on the Incorporation and Availability of Road Repair

The main novelty of the work in this paper arises from the incorporation of post-disaster road repair decisions into the pre-positioning network design process. Therefore, the first part of our computational experiments assesses the extent of the improvement resulting from this additional consideration, if any. In Figure 5, we report the percent deviations of each model from the best efficacy, equity, and robustness objectives under the cases with no repair and with repair activities starting immediately, one hour, and two hours after the beginning of the planning period. As expected, the best result for each objective is obtained when repair is immediately available.

Figure 5 shows that under the baseline instance settings, the case with no repair still produces feasible solutions. This is due to the fact that since complete blockage probabilities of the roads vary between 10% and 30%, the number of partially traversable roads is sufficient to guarantee a connected network. In disasters where more roads are completely blocked, the no-repair scheme may even be infeasible.

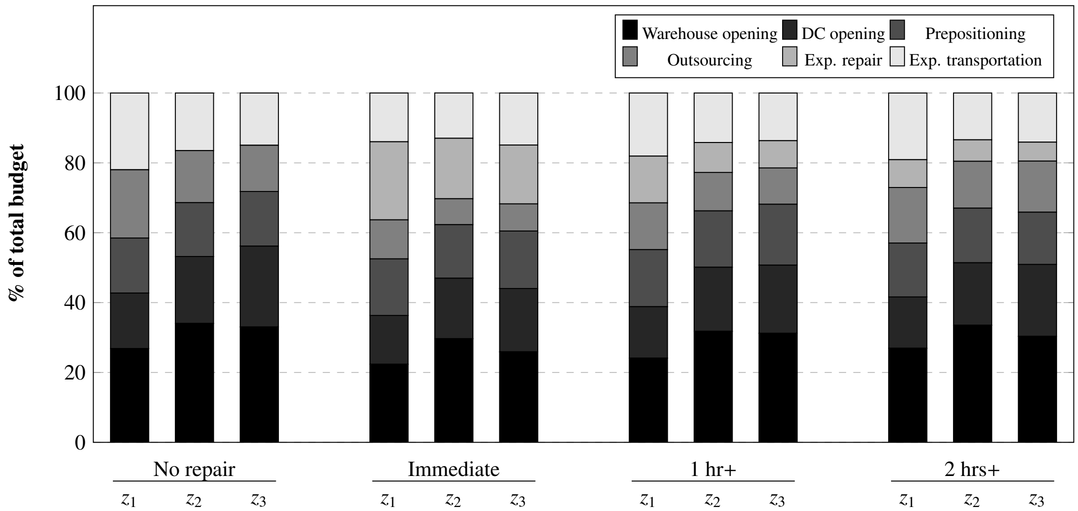

Figure 6: Percent breakdown of costs under each model and repair availability assumption

We also observe from Figure 5 that *under the efficacy, equity, and robustness objectives, the incorporation of post-disaster road repair improves the performance of pre-positioning network design by more than 18%, 13%, and 16%, respectively.* The improvement being larger for the efficacy objective can be attributed to the fact that each repair activity immediately contributes to the efficacy objective by improving the connectivity between at least one pair of nodes. On the other hand, improvement of the equity and robustness objectives requires that such an improvement should be made for the worst-off node pair. Hence, the marginal benefit of an additional repair activity is higher for the equity objective than that for the remaining two, leading to more significant improvements.

Another important policy-based implication of Figure 5 is that *for benefits of repair to be realizable, the activities should start as soon as possible following the disaster.* When repair activities start an hour into the response period, the improvements by repair reduce to 8%, 4%, and 6% for the efficacy, equity, and robustness objectives, respectively. When the availability is another hour later, the corresponding improvements are less than 2%, 1%, and 2%. Given that the inclusion of repair requires an increased level of coordination, late availability of repair may even be detrimental to the objective values in practice. This finding can be particularly generalized to pre-positioning network design at the district-level, where travel times are sufficiently low to ensure that a majority of deliveries can be made (possibly at inflated travel times) before repair becomes available.

To more thoroughly understand the structure of solutions, Figure 6 provides a percent breakdown of the fixed facility opening, item pre-positioning, expected item outsourcing, expected repair, and expected transportation costs for each of the solutions under varying objectives and with different repair assumptions. Since both budget constraints are binding for all models, the figure also provides a means for breaking down the total costs as well. An important pattern in Figure 6 is that *late or no availability of repair results in opening more facilities and pre-positioning more*

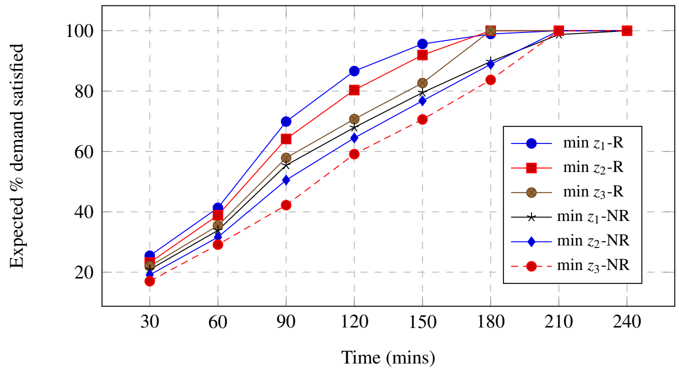

Figure 7: Expected percent of demand satisfied at given half-hour intervals for different models with/without the possibility of repair

items. This is an expected behavior, as the possible unavailability of part of the network requires that more items be stored to mitigate against later deliveries from farther away locations, due to increased travel times. If repair is available in a timely manner, such possibilities can be avoided, and thus fewer items are pre-positioned. A similar behavior is observed for transportation costs; *since more detours are needed, transportation costs are up to 80% higher for the no-repair case, compared to immediately available repair.* As expected, delayed availability of repair leads to less repair, and hence lower repair costs.

To shed light into how much of the deliveries are completed over time, Figure 7 provides the expected percentages of total weighted demand satisfied for half-hour intervals under the three objectives without repair and with immediately available repair. Using these discrete intervals, we deduce that *for the efficacy, equity, and robustness objectives, repair allows an average of 18%, 17%, and 17% more deliveries by any given time.* Furthermore, whereas models without repair finish the deliveries at an average of 202 minutes, this makespan reduces to an average of 169 minutes under repair. Thus, *the possibility of repair provides an average of 17% savings in the makespan over the three objectives.*

4.3.2 Results on Objective Function Selection

Regardless of repair, the choice of which objective function to use also affects the performance and structure of the resulting solutions. In choosing among the three objectives, we would like to ensure that not only should the selected objective provide a timely operation scheme, but the results under this objective should also perform reasonably well under the remaining two objectives. For this end, objective gaps can be derived from the percent deviations given in Figure 5.

The first finding regarding the objectives in Figure 5 is that under the given instance settings, *the objective gaps for the equity-based model outperform those of its efficacy- and robustness-based counterparts.* In particular, the average of the objective gaps $OG_{2|1}$ and $OG_{2|3}$ over the four repair/no-repair models are 4.5% and 2.3%, respectively. For the efficacy based model, average $OG_{1|2}$ and $OG_{1|3}$ are 11.4% and 13.0%; and for the robustness-based model, average

$OG_{3|1}$ and $OG_{3|2}$ are 18.2% and 9.5%, respectively. Hence, among the three alternative models, an equity-based model sacrifices the least from the remaining two objectives. When we consider the trends with the availability of repair, we observe that *as the availability of repair decreases, so do the objective gaps*. For instance, the average of the six aforementioned gaps is 16.5% when repair is immediately available, which reduces to 6.9% with no repair. This mainly arises from the fact that increasing availability of repair improves efficacy at a higher rate than equity and robustness, thereby leading to a higher discrepancy among the objectives.

When the cost breakdowns in Figure 6 are analyzed in detail, we observe similar trends for a given objective across different repair assumptions. Here, equity- and robustness-based models exhibit parallel behavior to each other. Regardless of the objective, *more facilities are opened and more items are pre-positioned under the equity- and robustness-based objectives*. This is in line with the intuition that to avoid the possibility of having to deliver to secluded DLs, which would substantially affect the objective functions, these modes act conservatively by opening more facilities and pre-positioning more items to serve more DLs from closer locations. Thus, *an equity-based model spends more time and cost on repair and transportation*, in order to decrease the travel times in a more reactive way.

Under different objectives, the delivery patterns over time also differ. Figure 7 shows that, as expected, *an efficacy-based model satisfies majority of the demand at a quicker rate*. For example, with repair, the equity- and robustness-based models make 92% and 84% of the total amount of deliveries by the equity-based model. However, *under equity or robustness objectives, delivery makespan is shorter than that under equity.* With repair, the makespan values are 181, 165, and 161 minutes for the efficacy-, equity-, and robustness-based models, whereas without repair these are 208, 201, and 198 minutes, respectively. Thus, more deliveries are made towards the end of the horizon with the latter two models.

4.3.3 Results on Assumptions Regarding Vulnerability

As the literature review suggests, road vulnerability (damage) can be modeled as increased travel costs, deflated road capacity, inflated travel times, and complete blockage. As time is of concern in this study, we incorporate the last two approaches. Figure 8 shows the changes in the objective function when no vulnerability is assumed, or road damage is incorporated as only travel time inflation or only complete/no damage. We also vary the vulnerability levels (probabilities that each road segment will be blocked) by evaluating 20% decrease (-20%) and increase (+20%) in the probabilities.

For the cases of no vulnerability, travel time inflation, and binary vulnerability assumptions, the deviations are from the objective value of the same level of vulnerability (-20%, base, or +20%) when both vulnerability types are present. For example, when only travel time inflation is assumed with +20% vulnerability and repair, the objective value is 5.48% more than that under +20% vulnerability and with repair when both travel time inflation and binary

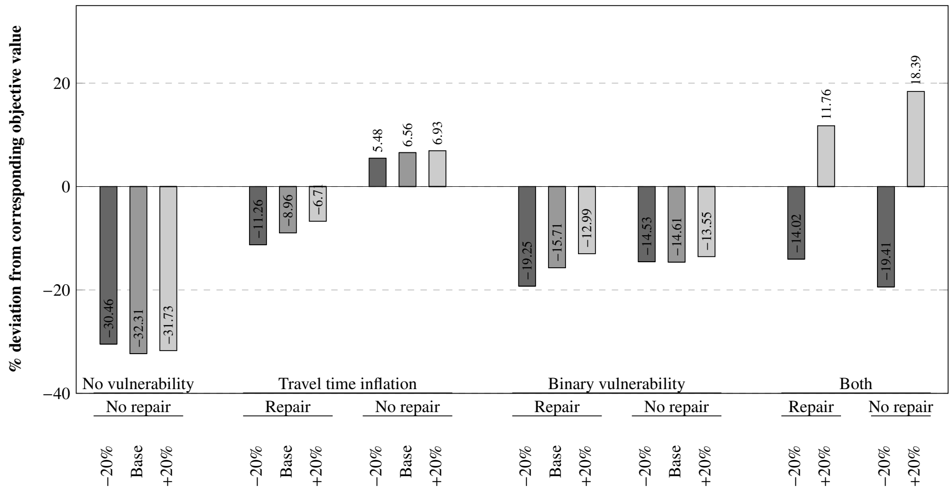

Figure 8: Assumption gaps for the cases where base vulnerability is unchanged, increased, or decreased by 20% and (i) no vulnerability is assumed, (ii) vulnerability is considered only as inflated travel times, and (iii) vulnerability is incorporated as complete or no damage from corresponding actual objective values with/without repair. For the last four columns, the deviations are from the base case.

vulnerability are assumed. The last four columns are deviations from the base case with both vulnerability types and repair. For example, when vulnerability is increased by 20% and with no repair, objective value increases by 18.39% compared to the base vulnerability level with repair.

From the base case results of Figure 8, one can infer that *completely ignoring the potential damage on the roads and facilities underestimates the objective value by more than 32%.* This substantial difference underlines the value of solving a more complicated model by incorporating vulnerability in at least some form. When only travel time inflation is considered, an interesting result is obtained. *With repair, assuming only travel time inflation tends to overestimate the objective value, whereas underestimating it when repair is available.* Without repair, although network connectivity is higher, travel times are overestimated. Since majority of the roads are not completely blocked in the actual case, this leads to an overall increase in travel times. *When only complete damage is possible, the objective is underestimated by around 15%.* This is expected, as this case assumes that most of the roads are traversable in their original travel times.

4.3.4 Results on Sensitivity to Parameter Values

The last part of our computational experiments relate to the sensitivity analysis of the results to vulnerability, budget, and capacity levels.

For an analysis of how changes in vulnerability levels affect the results, we first make use of the last four columns of Figure 8, where efficacy objective deviations for the case with 20% decrease and increase in road damage probabilities are given. When vulnerability is 20% lower, the objective value decreases by 14.0% and 19.4% with and without repair, respectively. The same values are 11.7% and 18.3% are higher with 20% higher vulnerability. These altogether imply that whereas *inclusion of repair increases robustness to changing vulnerability levels,* changes in the objective function

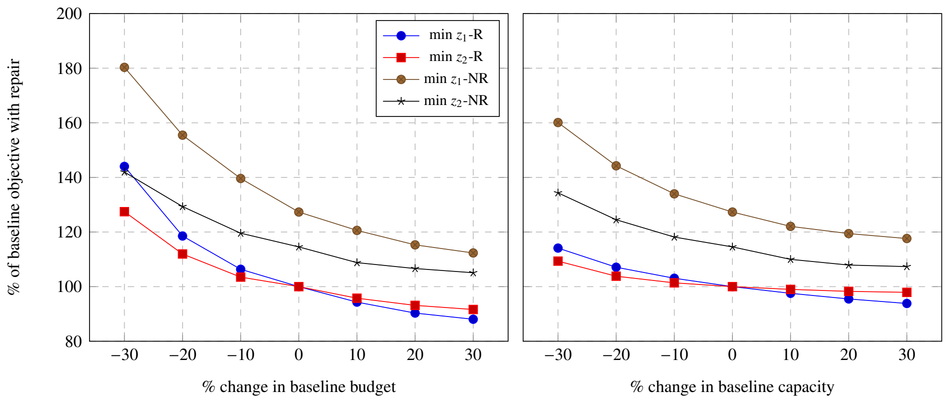

Figure 9: Percent deviation from corresponding baseline objective with repair for varying levels of budget and capacity

indicate that *accurate estimation of vulnerability is important for effectiveness of plans.*

Figure 8 also shows the assumption gaps of cases with different vulnerability assumptions and varying levels of vulnerability. When there is no repair, the inference is that results in Section 4.3.3 are still valid. However, *when repair is involved, the proposed model is more robust as vulnerability levels increase.* This is because as the number of damaged roads increase, the choice of which assumption is taken becomes weaker, and the resulting solutions resemble each other more.

Lastly, we observe the effect of changing budget and capacity levels on the efficacy- and equity-based models in Figure 9 by presenting the percent deviations from the original objective with repair when both budget and capacities vary from 70% to 130% of the original value in increments of 10%. As expected, the figure shows diminishing returns for both factors. However, as budget constraint is almost always binding, we observe that *the models are more sensitive to the budget than to the capacity, particularly so when repair is not involved.* Indeed, a 30% decrease in the budget leads to an average of 45% increase in the corresponding objective, whereas the same increase is around 28% for capacity.

5 Conclusions and Further Research Directions

This paper introduced the problem of designing a humanitarian inventory pre-positioning network under vulnerability by considering the pre-disaster decisions of facility location and item pre-positioning as well as post-disaster relief transportation and road repair activities in a concurrent manner. A two-stage stochastic program is formulated for an exact solution of the problem. For real-life based instances, the numbers of potential damage and demand scenarios deem the use of the exact solution impossible. To overcome this, a heuristic approach is developed based on an SAA scheme. The approach is further strengthened by the addition of a number of valid inequalities.

By means of computational experiments on a potential earthquake in Istanbul, Turkey, we show that (i) the SAA scheme is able to provide a timely and accurate approximation for the original two-stage stochastic program, (ii) the failure to incorporate road repair into the decision making process may lead to substantial losses for the timeliness of deliveries, (iii) an equity-based objective outperforms its counterparts in resolving the trade-off among these for this case, (iv) considering both types of vulnerability (complete damage as well as inflated travel times) may become particularly important if vulnerabilities are at lower levels, and (v) accurate estimation of vulnerability as well as allocation of sufficient budget may have crucial implications on obtaining effective results.

This paper also leads to interesting future research directions regarding the introduced problem. First, a timely solution to the SAA scheme requires that the resulting integer program be solved for a large number of scenarios. Even with the inclusion of valid inequalities, larger instances may require substantial amounts of computational time. To improve the accuracy of the SAA, the solution can be obtained by means of a heuristic approach, possibly using the integer L-shaped method or a specialized heuristic making use of the structural properties of the problem.

The definition of the problem involves a number of assumptions regarding road repair. First, we assume that sufficient number of repair resources exist, thus ignoring any potential scheduling aspects. Second, it is assumed that the resources can start the repair activities at the same time. While significantly increasing the complexity of the problem environment, relaxation of these assumptions is important for future work to better represent the real-life situation. Coordination among the repair and relief transportation entities is another challenge, which points to a separate area for future research. Lastly, the assumption of deterministic repair times can also be relaxed without substantial changes in the modeling and solution approach.

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