Locating Temporary Hospitals and Transporting the Injured Equitably in Disasters

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Abstract

In the aftermath of an earthquake, one of the most critical needs is medical care for the injured. A large number of individuals require immediate attention, often overwhelming the available healthcare resources. The sudden surge in demand, coupled with limited resources, route congestion and infrastructure damage, makes immediate medical care provision a significant challenge. This challenge intensifies when fairness concerns exist. Temporary hospitals help address the need for medical care when existing healthcare infrastructure is inadequate and road access is restricted due to congestion and damage. We develop a mathematical program to locate temporary hospitals, determine transportation routes, and allocate the injured efficiently and equitably. The impact of route congestion on transportation times is modeled using the Bureau of Public Roads (BPR) function. An exact approach based on Benders decomposition is employed to solve the resulting mixed-integer second-order cone program, with various acceleration techniques to enhance the method. This methodology is applied to test problems and the anticipated Istanbul Earthquake case study, focusing on aspects such as hospital capacities, candidate locations, road network disruptions, and varying injury severity levels. The goal is to construct a comprehensive healthcare response plan. Numerical results demonstrate the importance of a holistic approach to ensure low costs, manage congestion, and equitable provision of healthcare.

Keywords: disaster response, location of temporary hospitals, transportation of the injured, route assignment, equitable healthcare service, disruption, Benders decomposition, second-order cone programming, traffic congestion

1. Introduction

Earthquakes and other natural disasters cause severe causalities, economic loss and social costs. Growing world population and increased urbanization make population vulnerable to deaths and injuries from earthquakes and elevate the risk of mass casualties (Doocy et al, 2013). The immediate need for medical treatment created by mass casualties is one of the main challenges in emergency healthcare response.

The need for provision of satisfactory and prompt medical care arising in the aftermath of a disaster can be fulfilled by temporary field hospitals. These are mobile or modular facilities that function as back-ups when existing healthcare system cannot cope with the sudden-onset need and when road access is hindered by congestion or infrastructural damage. Temporary hospitals are possibly set up at public places such as schools or parks, which are considered as open and large enough areas to accommodate a considerable number of injured (Drezner, 2004). Establishment of temporary hospitals should take place in the early post-disaster phase so that a majority of the injured gets timely medical treatment. Where to locate temporary hospital units, how to allocate the injured to the hospitals, and which routes to take to carry the injured are decisions that have to be made immediately yet taking a holistic view. When making these decisions, limited resources at the existing healthcare facilities and disruption in the road network and infrastructure need to be considered. Hospitals should be located close enough to the affected areas since there are critical periods within which the injured must be treated. The critical period gets shorter as severity level of the injury increases (Kou and Wu, 2014). Multiple severity levels lead to multiple critical time periods, which affect the decisions on location of temporary hospitals as well as allocation of the injured to the hospitals. Furthermore, road accessibility should enable carriage of the injured within the critical time period, which necessitates minimal congestion on the routes. In the absence of a holistic assignment of injured to the routes, the evacuees might behave selfishly by selecting the shortest routes, ignoring the route selection of others. This would cause delays especially on the heavily utilized roads. A congestion control strategy, tailored for each injury class, would establish an efficient flow in the network.

Through this study we aim to address the following research questions:

1. In the wake of an earthquake, at which locations should temporary hospitals be set up?

2. Given the estimated number of injuries and possible disruption on road segments, injured should be transferred to which hospitals?

3. Equity in disaster relief is the extent to which all recipients receive comparable service (Huang et al. 2012). We aim to take into account critical time periods for different injury classes, while treating all injured within a class the same, in that transferring all victims in a injury-class within the critical time period of that class. To ensure an equitable transportation and minimal exposure to congestion, which routes should be taken by each injury class?

4. What are the drawbacks of decentralized route selection when compared to the systemic approach?

We develop a model that minimizes the cost of setting up temporary hospitals and transporting the injured to the hospitals while complying with the critical time periods under road congestion and disruptions. We use a scenario-based approach and analyze how decisions and performance measures change with each scenario. In the model the travel times are defined through the Bureau of Public Road (BPR) function which is a non-linear function of the flow over the route. The nonlinearity is handled through second-order cone (SOC) inequalities. Existence of multiple critical time periods lead to a mixed 0-1 SOC programming model. Numerical analysis show that for large-sized problems (such as the Istanbul earthquake) solving the model is not possible with off-the-shelf solvers. We resort to the Benders decomposition method to obtain reasonable solution times. The method is applied first to several well-known test problems, and then to the Istanbul earthquake case study. Our results show that Benders decomposition accelerated with introduced methods, outperform both off-the-shelf solvers and classical Benders' method in terms of time, especially for large size problems. Furthermore, findings highlight the importance of considering congestion in travel time calculations to improve equity in injured assignment.

The paper is organized as follows. In Section 2 we present the relevant literature, research gaps, and contribution of our paper. Sections 3 and 4 describe the structure of the medical evacuation network in detail and developed optimization model, respectively. The solution method and accelerated Benders decomposition method are presented in Sections 5 and 6, respectively. In Section 7, we deal with the experiments on some test problems and Istanbul case study and make sensitivity analysis of the obtained results. Finally, the conclusion and directions for future studies are summarized in section 8.

2. Literature Review

We review studies on locating temporary hospitals, congestion planning, disruption considerations in the face of a disaster, and managing equitable provision of healthcare relief to the injured.

Facility location for temporary hospitals and transferring injured to the hospitals. In disaster planning, especially when locating facilities such as hospitals, it is crucial to consider future uncertainties. Some past work study this problem in the absence of uncertainty, and determine the locations of the temporary hospitals by p-center, p-median or coverage models (Jia et al., 2007, Lu and Hou, 2009, Yi and Ozdamar, 2007). Jia et al. (2007) address hospital location problem in the presence of large-scale emergencies and show reduction in mortality and economic loss with the suggested model. Lu and Hou (2009) extend the problem in Jia et al. (2007) to a maximal covering problem with specific quantity-of-coverage requirements for multiple facilities. The proposed Ant Colony Optimization (ACO) algorithm provides a highly effective solution. Yi and Ozdamar (2007) develop a comprehensive model for selecting temporary emergency centers, aiming to maximize medical coverage in disaster-affected areas and optimally distribute medical staff between temporary and permanent emergency response units.

In those work that take uncertain nature of disasters into account when locating temporary hospitals, typically a scenario-based approach is adopted. Acar and Kaya (2019) introduce a two-stage scenario based stochastic programming model for location and relocation of mobile hospitals in pre- and post-stages of a disaster. Shishebori and Babadi (2015) develop a mixed integer linear programming model for locating medical service centers in a robust and reliable way. The model comprehensively addresses uncertainties stemming from system disruptions, and consider the limitations in the investment budgets. Revelle et al. (1997) propose various coverage models to guarantee that demand nodes and any established facilities are backed-up by other facilities. These models are designed with the understanding that in the event of a disaster, local emergency services might become non-functional or unreachable, necessitating coverage from facilities in other areas.

Some past works investigate the challenges of joint medical center location and injured transportation. Salman and Gul (2014) model field hospital deployment, capacity allocation and casualty transportation to minimize the total cost and the travel and waiting time of casualties' subject to the service capacity at hospitals and the availability of vehicles. Aydin (2016) presents a two-stage stochastic model to identify the optimum number and locations of field hospitals and the allocation of injured to hospitals considering disruptions. The model is applied to the Istanbul earthquake case. Liu et al. (2019) focus on facility location and casualty allocation where survival probabilities are assumed to be decreasing over time, with a trade-off between minimizing the operational cost and maximizing the number of survivors. Oksuz and Satoglu (2020) formulate a two-stage stochastic programming model to determine the location of temporary medical centers and to assign the injured while considering damage to hospitals and roads. Gao et al. (2017) develop a hybrid genetic algorithm to optimize the location and allocation of temporary emergency medical service centers in disaster response, where the aim is to minimize total travel time and patient mortality risk. The effectiveness of the approach is illustrated with scenarios modeled on the Portland area. Landa-Torres et al. (2013) address a facility location problem focused on the strategic deployment of 24-hour emergency resources, selecting optimal sites within potential healthcare centers, and efficiently directing patients to these resources. Chen and Yu (2016) use an integer programming and network-based partitioning to identify locations of temporary Emergency Medical Service (EMS) in disaster scenarios. Disaster-induced and regular demands, transportation infrastructure as well as existing EMS are taken into account. Their method allows for detailed demand assessment at individual victim level. Wang et al. (2020) explore a dynamic post-disaster emergency planning problem where selection of medical centers along with the allocation of injured within a critical time are under consideration. A metaheuristic algorithm is developed to solve the problem. Sun et al. (2021) present a robust optimization model for locating emergency facilities and transporting disaster casualties, considering the variability in casualty numbers and their deteriorating injuries. Finally, a line of past work focus on how injured should be transported from the affected areas to medical facilities to reduce waiting time or fatalities and transportation cost in the wake of a large-scale emergency (see, Gharib et al. 2021, Shavarani and Vizvar, 2018, Wilson et al. 2013, Kula et al. 2012).

Congestion planning during disasters. Under emergency conditions, managing congestion in transportation becomes a critical aspect of emergency relief. To our knowledge, there exists a limited number of studies on provision of healthcare relief during a disaster with congestion considerations. Cui et al. (2014) study the distribution pattern of evacuation flow on a road network where travel time on each arc is modeled as a BPR function. Chiou and Lai (2008) explore the optimal relief path and traffic controlled arcs in an uncertain post-disaster environment. Authors develop an integrated multi-objective model composed of shortest path, flow assignment and arc selection. Li et al (2012) select shelter locations incorporating drivers' route choice and equilibrium-based traffic dynamics for hurricane events. Computational results on a case study demonstrate the importance of jointly considering shelter location and needs and behavior of evacuees.

Chou et al. (2022) aim to enhance Emergency Medical Service (EMS) response efficiency in Mass Casualty Incidents (MCIs) by addressing delays due to traffic congestion and hospital capacity. The authors develop a patient transportation and assignment model with ambulance routing. Wu and Chen (2023) determine the optimal number of EMS vehicles needed using dynamic traffic assignment while accounting for both hospital-bound severely injured people and trips by dislocated residents. Chang et al. (2023) determine the locations of casualty collection points and the allocation of EMS resources under time-varying traffic congestion for mass casualty incidents. They utilized the speed-density function, which includes stochastic traffic flow speed and stochastic travel time for each road segment, to calculate travel times reflecting road conditions and traffic after disaster. Bayram et al. (2015) and Bayram and Yaman (2018) address traffic management during evacuations, optimizing shelter locations and assigning evacuees to minimize total evacuation time. They utilize BPR functions and employ second-order cone programming (SOCP) techniques to handle nonlinear mixed integer programming models efficiently.

Facility and road disruptions. When deciding on location of temporary hospitals and devising routes for transporting the injured, it is crucial to consider disruptions to road networks and facilities. Acar and Kaya (2019) in their study locate mobile hospitals considering that the existing hospitals might be damaged during the disaster. For relief transportation, Salman and Yucel (2010) take network failure into account and show that considering failure dependence of links improves the demand coverage in Istanbul earthquake case study. Ahmadi et al. (2015) develop a two-stage stochastic model for locating local depots and routing after an earthquake, taking network failure, relief time and cost of unsatisfied demand into account. Barbarosoğlu and Arda (2004) construct a two stage multi-commodity and multi-modal network flow model for emergency response, where road damage is modeled through reduced arc capacities. Mohamadi and Yaghoubi (2017) determine the location of transfer points and distribution centers before earthquake and allocate the injured to hospitals after the earthquake, incorporating failure probabilities of distribution centers and routes.

Equitable provision of healthcare relief. Providing equitable access to services is one of the primary concerns when designing humanitarian operations. Muggy and Stamm (2017) address location of temporary healthcare facilities to provide treatment during infectious disease outbreaks. The authors ensure equitable provision of care with sufficient access to all demand locations. Repoussis et al. (2016) study an integrated ambulance dispatching, patient assignment and treatment ordering problem, while fairness is ensured by minimizing the latest response. In the context of evacuation during a disaster, Bayram et al. (2015) and Bayram and Yaman (2018) determine locations of shelters and ensure fair assignment of evacuees to shelters by putting a limit on the length of feasible evacuation routes. Aringhieri et al. (2022) optimize ambulance routes in post-disaster scenarios. The authors formulate the problem as a new variant of the Team Orienteering Problem with hierarchical objectives, balancing efficiency and equity. In the model, equity is defined as ensuring impartiality and fairness in delivering relief services, with the goal of minimizing the maximum waiting time for red patients suffering from serious injuries to provide equal services.

Zhu et al. (2019) develop models for emergency relief routing for injured with varying degrees. A relative deprivation cost is defined to ensure fairness and tolerable suffering duration is used as the critical time in determining priorities. Their model address fairness issues among victims in different affected areas by minimizing the absolute deviations between deprivation costs across disaster regions.

Our work is closest to Bayram and Yaman (2018a,2018b) and Oksuz and Satoglu (2020). In Oksuz and Satoglu (2020) temporary hospitals are located before the earthquake while injured are transferred after the earthquake. Equitable carriage and route congestion are not considered and critical time period is equivalent to a distance limit. We assume the location of temporary hospitals are set after the earthquake considering possible damages to road segments and hospitals. Addressing location, allocation, and route assignment while taking into account congestion, disruptions, and equitable carriage are key considerations. We develop an exact and efficient methodology to solve the MISCOP problem and to verify the applicability of the model. Bayram and Yaman (2018a,b) discuss the problem of shelter location and evacuation under road congestion in the wake of an earthquake and Bayram and Yaman (2018a) develop a Benders decomposition based algorithm to solve the scenario-based two-stage stochastic programming approach. The Istanbul earthquake is considered as a case study. In Bayram and Yaman (2018b) off-the-shelf solver is used and the value of stochastic solution is assessed. Our study deals with the location of temporary hospitals to deliver health service to those in need in the wake of an earthquake disaster. We address two objectives; cost and equitability of service, where the latter is measured through the maximum time it takes to reach the hospital. We further propose class-based critical time period for casualty classes that improves efficient usage of resources while ensuring the fairness criterion to be fully met. Usage of separate critical time periods for multiple injury classes that use common road segments on the routes leads to an MISOCP, increasing the problem complexity significantly.

Therefore, Benders decomposition algorithm is proposed as an exact solution method. We present a taxonomy of closest work in Table 1.

Table1. A summary of recent studies on hospital location and injured transportation

Solution Approach			**Considerations**							**Decisions**			
Meta/Heuristic Algorithms	**Exact Approach**	**Off-the-shelf solver**	**Critical time limit**	**Prioritization**	**Traffic**	**Equity**	**Distance**	**Time**	**Cost**	**Injured Transportation**	**Allocation**	**Location**	**Authors**
*												*	Salman and Yucel (2010)
*					*			*				*	Li et al (2012)
		*				*		*				*	Acar and Kaya (2019)
*					*			*		*			Chiou and Lai (2008)
	*				*			*	*	*			Cui et al. (2014)
	*				*	*		*		*		*	Bayram and Yaman (2018)
	*				*	*		*		*		*	Bayram et al. (2015)
		*									*	*	Jia et al. (2007)
*											*	*	Lu and Hou (2009)
		*						*	*	*	*	*	Salman and Gül (2014)
										*		*	Aydin (2016)
*				*					*	*		*	Liu et al. (2019)
*					*			*		*			Li and Ozbay (2015)
*	*			*				*		*	*		Repoussis et al. (2016)
		*		*		*			*	*		*	Oksuz and Satoglu (2020)
		*		*						*	*	*	Yi and Özdamar (2007)
		*				*			*		*	*	Shishebori and Babadi (2015)
*				*				*	*		*		Gharib et al. (2021)
*			*	*						*			Shavarani and Vizvari (2018)

*				*				*			*	*	Gao et al. (2017)
	*								*			*	Chen and Yu (2016)
*							*		*		*	*	Wang et al. (2020)
		*	*	*							*	*	Sun et al. (2021)
*			*	*	*				*	*			Zhu et al. (2019)
*				*				*		*			Kula et al. (2012)
*							*		*		*	*	Landa et al. (2013)
*								*			*		Chou et al. (2022)
*					*			*		*			Wu and Chen (2023)
	*							*			*		Chang et al. (2023)
*				*		*		*		*			Aringhieri et al. (2022)
*	*		*	*	*	*	*	*	*	*	*	*	**Our study**

3.Problem Description

We consider the problem of establishing temporary hospitals and identifying the routes to carry the injured to the temporary and permanent hospitals in the early post-disaster phase of an earthquake.

Temporary hospitals are constructed after the earthquake at the candidate locations, which are schools in our study. The capacity of each temporary hospital is defined along with the space in the school and is determined before the earthquake. The number of temporary hospitals that can be established is assumed to be limited due to the budget restrictions and the limited number of personnel. For permanent hospitals, it is assumed that capacity (defined in number of beds) is already partly allocated to inpatients.

The injured are classified into two as “heavily injured” and “moderately injured”, where the former correspond to the urgent victims in need of an immediate medical care, while the latter, even though requiring a care and life-saving intervention, have less urgency. These two classes are differentiated by their “critical time periods,” named as time-windows in the remainder of the text, which indicates an upper bound on the time to reach the hospital

All injured individuals are carried to the hospitals via ambulances, with each ambulance accommodating a single injured person. Given the finite number of rescue personnel available, it is not possible to evacuate all injured individuals simultaneously; rather, it must be done gradually over time. To balance transportation with the rescue rate, we divide the transportation horizon into evenly spaced periods. Specifically, the number of periods is determined by the rescue force's rate of response (1 divided by the rescue rate). During each period, an equivalent number of rescue personnel are available and an equivalent number of injured are carried. The underlying assumption is that there are adequate number of ambulances and once ambulances carries the injured, rescue forces will be ready for the next period. The time-windows are defined with respect to the beginning of each time period. The duration of each period is set as 1 hour that provides sufficient time for both rescue operations and ambulance dispatch. The capacities of the hospitals to accept the injured are also modified in accordance with the periodic approach in that the total capacity of the hospital is divided by total number of periods. This gives us the periodic service capacity for a hospital.

We define a network where the arcs represent the road segments and the nodes represent affected areas, hospital locations and junctions of the road segments. A route from an affected area to a hospital possibly spans multiple road segments.

The routes selected by each injury class might differ. A road segment might be shared by multiple routes. The carrying capacity of a segment is defined by the number of vehicles that travel at the base (free flow) travel time. If the flow exceeds the road capacity, congestion occurs and time spent on that segment increases. The travel time under congestion is expressed through the BPR function (TAM, 1964):

$$t(x) = t^0\ (1+\alpha \left(\frac{x}{c}\right)^{\beta}) \qquad (1)$$

where $t(x)$ is the travel time of the road segment (which is unidirectional) on which flow volume is x, t^0 is the base travel time (at zero volume), c is the carrying capacity, maximum number of vehicles (with equal velocities) that can pass through the road segment under free flow conditions and α, β are the shape factors defined based on the characteristics of the road segment.

Our aim is to determine what fraction of the injured in each class in each affected area should be carried through which route and to which hospital. This decision is made jointly with the location decisions of temporary hospitals, considering the capacities of the hospitals (after the earthquake), the travel time of the routes (which is a function of the flow, and the carrying capacity after the earthquake) and the time windows. The objective is to minimize the total cost due to setting up temporary hospitals and due to transportation of the injured to the hospitals, while meeting the capacity and time window limits. We assume there exist penalties due to not being able to accommodate the injured at the permanent hospitals and due to any violation of the time windows.

An earthquake is defined by many scenarios depending on the epicenter and the magnitude. An earthquake scenario is characterized by the number and the severity of the injuries and capacity of the existing permanent hospitals and arcs. Considering possible earthquake scenarios, we provide a response plan for the early post-disaster decisions, which would allow for a quick response when an earthquake hits (see Barbarosoğlu and Arda 2004, Salman and Gül 2014, Bayram and Yaman 2018a, 2018b, for similar scenario-based approaches).

4. Mathematical Model

Let G = (V, Z) be the network with vertex set V where $V = A \cup J \cup P$, and arc set Z, $(v_1, v_2) \in Z, v_1, v_2 \in V$. In V, A is the set of affected areas, J is the set of hospitals, and P is the set of junction nodes where arcs meet. Each affected area corresponds to a demand node for each injury class. $J = H \cup H'$, where H denotes the set of existing hospitals and H' the candidate temporary hospitals. Set of arcs that form a path between each affected area-hospital pair defines a route. Set of all routes between an area (a) and hospital (j) pair is denoted with R_{aj}. Injury classes are denoted with $i \in I = \{1,2\}$ where 1 represents the heavily injured and 2 represents the moderately injured. np_{ai} is the number of injured with injury level *i* in affected area *a*.

To ensure tractability, a set of eligible routes are identified between each area-hospital pair for each injury class i. Let this set be denoted with R_{aji}.To identify eligible routes, a tolerance degree (λ), the coverage radius of hospitals (cvr) and the time window of each injury class (tw_i) are considered. Let ds_r denote the length of route r. First, for each area-hospital pair, the shortest possible route is identified, length of which is denoted with $ds^*_{aj} = \min_{r \in R_{aj}} \{ds_r\}$. The tolerance degree (λ) ensures that the routes that are $(1 + \lambda)$ times longer than the shortest route are not considered (see Bayram et al.,2015 for a similar approach). It is assumed that each hospital can provide medical services to areas within a coverage radius, cvr. Finally, let t^0_r denote the base travel time of a route $r \in R_{aj}$. For injury class i, if base travel time of route r (t^0_r) exceeds the time window (tw_i) by a factor of σ, then that route is considered as non-eligible for that class. Note the travel time depends on the distance and the velocity (ve). Then,

$$R_{aji} = \left\{ r \in R_{aj} \middle| ds_r \leq \min\left\{(1 + \lambda) ds^*_{aj}, \ \sigma tw_i \, ve \, , cvr\right\}\right\} \quad (2)$$

Table 2 lists the notation used in the model.

Table 2. Notation

Sets

A: Set of affected areas (demand nodes), a= 1, … ,$|A|$
H: Set of permanent hospitals, h= 1, …, $|H|$
H′: Set of temporary hospitals, h′= 1, …, $|H|$
J: Set of hospitals, j = 1, … , $|J|$ where H ∪ H′=J
I: Levels of injury: 1: heavily injured, 2: moderately injured
R: Set of all eligible routes, r = 1, … , $|R|$
a_r: Area of route r, $a_r \in A$
j_r: Destination hospital of route r, $j_r \in J$
R_i: Set of routes eligible to be used by people with injury level i (note $R_1 \cap R_2 \neq \emptyset$)
R_a: Set of routes that have area a as the origin point, $R_a \subseteq R$
R_{ai}: Set of eligible routes for origin area a and injury class i $R_{ai} = R_a \cap R_i$
R_j: Set of eligible routes that have hospital j as the destination poin $R_j \subseteq R$
R_{ji}; Set of eligible routes to hospital j that can be to be used by people with injury level i, $R_{ji} = R_j \cap R_i$
R_{aji}: Set of eligible routes between area a and hospital j for injury $R_a \cap R_j \cap R_i$
Z**:** Set of all arcs, z = 1, … ,$|Z|$
Z_r: Set of arcs on eligible route r, $Z_r \subseteq Z$
R_z: Set of eligible routes of which arc z is a part, $R_z \subseteq R$
R_{zi}: Set of eligible routes to be used by people with injury level i of which z is a part, $R_{zi} = R_z \cap R_i$

Parameters

cap_j: Admission capacity (service rate) of hospitals
c_z: hourly capacity of arc z (maximum number of injured that can flow in 1 hour)
ds_r: Length of route r
ds^*_{aj}: Length of shortest route between area a and hospital j, $ds^*_{aj}= Min_{r\in R_{aj}}\{ds_r\}$
fo_j: Fixed cost of opening temporary hospital j, j ∈ H′
ct: Transportation cost per injured carried per unit distance
ce_j: Cost of exceeding the capacity for hospital j, j ∈ H
cp_i: for injury level i, penalty incurred for exceeding the time window per unit time
np_{ai}: Number of people with injury level i in area a
t^0_z: Base travel time of arc z at zero volume
tw_i: Time window for people with injury level i
n: Maximum number of temporary hospitals
oc_z*:* Preoccupied capacity of arc z

Decision variables

E_{ri}: number of people with injury level i in area a_r using route r, by $np_{a_r i}$
X_z: Volume of arc z
Y_j: 1 if temporary hospital j is established, 0 otherwise , j∈ H′
W_r: 1 if route r is used, 0 otherwise, $r \in R$
U_j: Amount of violated capacity for hospital j, j∈ H
V_i: Maximum amount of violation of time window for people with injury level i

(Location and Transportation (LAT))

$$\text{Min} \sum_{j\in H'} fo_j Y_j + ct \sum_i \sum_{r\in R_i} E_{ri} np_{a_r i} ds_r + \sum_{j\in H} ce_j U_j + \sum_i cp_i V_i \tag{3}$$

$$\sum_{r\in R_{ai}} E_{ri} = 1 \qquad \forall\, a \in A, \forall\, i \in I \tag{4}$$

$$\sum_i \sum_{r\in R_{ji}} E_{ri} np_{a_r i} \le cap_j\, Y_j \qquad \forall j \in H' \tag{5}$$

$$\sum_i \sum_{r\in R_{ji}} E_{ri} np_{a_r i} \le cap_j + U_j \qquad \forall j \in H \tag{6}$$

$$E_{ri} \le W_r \quad \forall\, i \in I, \forall\, r \in R \tag{7}$$

$$X_z = \sum_i \sum_{r\in R_{zi}} E_{ri} np_{a_r i} + oc_z \quad \forall\, z \in Z \tag{8}$$

$$\sum_{j \in H'} Y_j \leq \mathrm{n} \tag{9}$$

$$\sum_{z \in Z_r} t_z^0 \left(1 + \alpha \left(\frac{X_z}{c_z}\right)^{\beta}\right) \leq tw_i + V_i + M\,(1 - W_r) \quad \forall\, i \in I, \forall\, r \in R_i \tag{10}$$

$$E_{ri}\,, X_z, U_j, V_i \geq 0,\, Y_j\,, W_r \in \{0,1\} \;\; \forall\, r \in R, \forall\, i \in I, \forall\, z \in Z, \forall\, j \in H' \tag{11}$$

Objective function minimizes the total cost of opening temporary hospitals, transferring the injured to hospital, violated capacity of permanent hospitals and violated time, for different injury levels. Constraint (4) ensures all injured are carried to the hospitals. Constraints (5) and (6) impose limitation on capacity of hospitals. Constraint (7) forbids transferring the injured through the route that is not selected. Constraint (8) calculates volume of each arc including capacity preoccupied by other vehicles. Constraint (9) enforces the limitation on number of open temporary hospitals. Constraint (10) limits total travel time of routes used by different injury class to time window for each class. Constraint (11) is variable restrictions.

We assume $\beta = 2$, which makes Constraint (10) nonlinear. The model is a mixed integer nonlinear programming model. Motivated by the advances in second order cone programming (Ben-Tal and Nemirovski, 2001, Alizadeh and Goldfarb, 2003), the model is reformulated as MISOC program.

By defining auxiliary variable Q_z and adding inequality (12), the nonlinearity is transferred from Constraint (8) to Constraint (10), as follows:

$$X_z^2 \leq Q_z \qquad \forall\, z \in Z \tag{12}$$

$$\sum_{z \in Z_r} t_z^0 \left(1 + \alpha \frac{Q_z}{{c_z}^2}\right) \leq tw_i + V_i + M\,(1 - W_r) \quad \forall\, i \in I, \forall\, r \in R_i \tag{13}$$

$$Q_z \geq 0 \qquad \forall\, z \in Z \tag{14}$$

(12) is a hyperbolic inequality that can easily be converted to a second-order cone inequality. The respective quadratic cone constraints are:

$$\left\| 2X_z, Q_z - 1 \right\| \leq Q_z + 1 \qquad \forall\, z \in Z \tag{15}$$

Equivalently:

$$(2X_z)^2 + (Q_z - 1)^2 \leq (Q_z + 1)^2 \qquad \forall\, z \in Z \tag{16}$$

Let $X_z^{'}$ denote $2X_z$, σ_z denote $Q_z - 1$ and φ_z denote $Q_z + 1$. Then Equation (16) is expressed equivalently as:

$$X'_z{}^2 + \sigma_z{}^2 \le \varphi_z{}^2 \qquad \forall\, z \in Z \tag{17}$$

$$-X'_z + 2X_z = 0 \qquad \forall\, z \in Z \tag{18}$$

$$-\sigma_z + Q_z = 1 \qquad \forall\, z \in Z \tag{19}$$

$$-\varphi_z + Q_z = -1 \qquad \forall\, z \in Z \tag{20}$$

$$Q_z, X'_z, \sigma_z, \varphi_z \ge 0 \quad \forall\, z \in Z \tag{21}$$

5. Solution Method

The LAT is a MISOCP model whose reasonable sizes can be solved with off-the-shelf solvers. Our preliminary analysis shows that for real-size problem instances (such as the Istanbul case), solution times can be as high as 7 hours. Since it is crucial to obtain a solution in a short amount of time after an earthquake, we propose an exact solution approach based on the Bender's decomposition algorithm.

In the Benders decomposition algorithm, the problem is decomposed into a master problem and a subproblem. When the decision variables of the subproblem are all continuous, the Benders decomposition algorithm is known to converge in a finite number of iterations. The LAT is decomposed into the Master Problem (MP) and the Primal Subproblem (PSP) as follows:

(MP)

$$\text{Min} \sum_{j \in H'} fo_j Y_j \tag{22}$$

$$\sum_{j \in H'} Y_j \le \text{n} \tag{23}$$

$$Y_j, W_r \in \{0,1\} \qquad \forall\, j \in H', \forall\, r \in R \tag{24}$$

(PSP)

$$\text{Min } ct \sum_i \sum_{r \in R_i} E_{ri} np_{a_r i} ds_r + \sum_{j \in H} ce_j U_j + \sum_i cp_i V_i \tag{25}$$

$$\sum_{r \in R_{ai}} E_{ri} = 1 \qquad \forall\, a \in A, \forall\, i \in I \tag{26}$$

$$\sum_i \sum_{r \in R_{ji}} E_{ri} np_{a_r i} \le cap_j \bar{Y}_j \qquad \forall j \in H' \tag{27}$$

$$\sum_i \sum_{r \in R_{ji}} E_{ri} np_{a_r i} \le cap_j + U_j \qquad \forall j \in H \tag{28}$$

$$E_{ri} \le \overline{W}_r \quad \forall\, i \in I, \forall\, r \in R \tag{29}$$

$$X_z = \sum_i \sum_{r \in R_{zi}} E_{ri} np_{a_r i} + oc_z \quad \forall\, z \in Z \tag{30}$$

$$\sum_{z \,\epsilon Z_r} t_z^0 \left(1 + \alpha \frac{Q_z}{C_z^2}\right) \le tw_i + V_i + M\,(1 - \overline{W}_r) \qquad \forall\, i \in I, \forall\, r \in R_i \tag{31}$$

$$X'_z{}^2 + \sigma_z{}^2 \le \varphi_z{}^2 \qquad \forall\, z \in Z \tag{32}$$

$$-X'_z + 2X_z = 0 \qquad \forall\, z \in Z \tag{33}$$

$$-\sigma_z + Q_z = 1 \qquad \forall\, z \in Z \tag{34}$$

$$-\varphi_z + Q_z = -1 \qquad \forall\, z \in Z \tag{35}$$

$$E_{ri}\,, X_z, U_j, V_i,\ Q_z, X'_z, \sigma_z, \varphi_z\ \geq 0 \quad \forall\, r \in R, \forall\, i \in I, \forall\, z \in Z, \forall\, j \in H' \tag{36}$$

Note the decision variables Y_j and W_r of the (MP) become parameters for the (PSP), which we denote with $\bar{Y}_j$ and $\bar{W}_r$.

In this model, time window constraint (31) is modelled through Big-M coefficients, which typically results in poor optimality cuts. To remove the dependency on the Big-M coefficients we replace (31) with constraint (37).

$$\bar{W}_r \sum_{z\,\epsilon Z_r} t_z^0 \left(1 + \alpha \frac{Q_z}{C_z^2}\right) \leq\ tw_i\ + V_i \qquad \forall\, i \in I, \forall\, r \in R_i \tag{37}$$

Note the subproblem is a Second Order Cone Programming (SOCP) problem with continuous variables. For the Bender's decomposition algorithm, we first take the dual of (PSP). The Dual Subproblem (DSP) is formulated as follows:

(DSP)

$$\text{Max}\ \sum_a \sum_i b_{ai} + \sum_{j\in H'} cap_j\, \bar{Y}_j\, g_j^{(1)} + \sum_{j\in H} cap_j\, g_j^{(2)} + \sum_i \sum_{r\in R_i} \left[\bar{W}_r \sum_{z\,\epsilon Z_r} (-t_z^0) + tw_i\right] k_{ir}^{(1)} + \sum_i \sum_{r\in R_i} \bar{W}_r k_{ir}^{(2)} + +\sum_z \left(s_z'^{(3)} - s_z'^{(4)}\right) \tag{38}$$

$$b_{ai} + np_{a_r i} g_j^{(2)} + k_{ir}^{(2)} - \sum_{z\in Z_r} np_{a_r i} s_z'^{(1)} \leq ct.np_{a_r i}\,.ds_r \qquad \forall\, a \in A, \forall\, j \in H, \forall\, i \in I, \forall\, r \in R_{aji} \tag{39}$$

$$b_{ai} + np_{a_r i} g_j^{(1)} + k_{ir}^{(2)} - \sum_{z\in Z_r} np_{a_r i} s_z'^{(1)} \leq ct.np_{a_r i}.ds_r \qquad \forall\, a \in A, \forall\, j \in H', \forall\, i \in I, \forall r \in R_{aji} \tag{40}$$

$$s_z'^{(1)} + 2s_z'^{(2)} \leq 0 \qquad \forall\, z \in Z \tag{41}$$

$$\frac{t_z^0 \alpha}{C_z^2} \sum_i \sum_{r\in R_{iz}} k_{ir}^{(1)} + s_z'^{(3)} + s_z'^{(4)} \leq 0 \qquad \forall\, z \in Z \tag{42}$$

$$-g_j^{(2)} \leq ce_j \qquad \forall\, j \in H \tag{43}$$

$$-k_{ir}^{(1)} \leq cp_i \qquad \forall\, i \in I, \forall\, r \in R_i \tag{44}$$

$$\left(s_z'^{(2)}\right)^2 + \left(s_z'^{(3)}\right)^2 \leq \left(s_z'^{(4)}\right)^2 \qquad \forall\, z \in Z \tag{45}$$

$$s_z'^{(1)}, s_z'^{(2)}, s_z'^{(3)}\ \text{URS}\ \ \forall\, z \in Z \tag{46-a}$$

$$g_j^{(1)} \leq\ 0 \quad \forall\, j \in H \tag{46-b}$$

$$g_j^{(2)} \leq\ 0 \quad \forall\, j \in H' \tag{46-c}$$

$$k_{ir}^{(1)}, k_{ir}^{(2)} \leq 0\ \ \forall\, i \in I, \forall\, r \in R_i \tag{46-d}$$

b_{ai} URS $\forall\, a \in A, \forall\, i \in I$ (46-e)

$s_z'^{(4)} \geq 0 \;\; \forall\, z \in Z$ (46-f)

where b_{ai}, $g_j^{(1)}$, $g_j^{(2)}, k_{ir}^{(2)}$, $s_z'^{(1)}, k_{ir}^{(1)}$, $s_z'^{(2)}, s_z'^{(3)}, s_z'^{(4)}$ are dual multipliers associated with constraints (26-31) and (33-35), respectively. The objective function of the dual subproblem provides a cut to the master problem. Hence, the cut is incorporated into (MP) as follows:

$$\text{Min} \textstyle\sum_{j \in H'} fo_j Y_j + \emptyset \tag{47}$$

$$\textstyle\sum_{j \in H'} Y_j \leq \text{n} \tag{48}$$

$$\phi \geq \textstyle\sum_a \sum_i b_{ai} + \sum_{j \in H'} cap_j \, Y_j g_j^{(1)} + \sum_{j \in H} cap_j \, g_j^{(2)} + \sum_i \sum_{r \in R_i} \left[W_r \sum_{z \,\epsilon Z_r} (-t_z^0) + tw_i\right] k_{ir}^{(1)} + \sum_i \sum_{r \in R_i} W_r k_{ir}^{(2)} + \sum_z \left(s'^{(3)}_z - s'^{(4)}_z\right) \tag{49}$$

$Y_j, W_r \in \{0,1\} \; \forall j \in H', \forall r \in R$ (50-a)

ϕ URS (50-b)

Note, in (49), the decision variables of the (DSP) become parameters, while the parameters $\bar{Y}_j$ and $\bar{W}_j$ become decision variables. The parameters are updated in every iteration of the algorithm.

6. Experimental Study

Before obtaining the results for the İstanbul earthquake case study, we work on several acceleration techniques for the Bender's decomposition algorithm. A straightforward application of the classical Benders method may fail to converge in a reasonable time, possibly due to generation of low-quality cuts, ineffective initial iterations or the complexity of the subproblem. Our proposed techniques aim to alleviate these inefficiencies. Among several acceleration techniques, we select the best performers and use the most promising one for the Istanbul case study. Besides the acceleration techniques we also suggest a heuristic method, that improves the solution time at the expense of finding the optimal solution. We first describe the acceleration techniques and the heuristic, and then present their performances. In Section 7, we present the case study in details.

6.1 Acceleration Techniques

For accelerating the Bender's algorithm, the following are proposed: (i) warm start, (ii) decomposition and (iii) valid inequalities. A warm start corresponds to a well-performing initial solution for the master problem. We propose 4 initial solutions. For decomposition, the approach is based on introduction of auxiliary variables. For valid inequalities, two approaches are proposed; namely, iterated lower bound and fixed lower bound. In total, 4 initial solutions are combined with decomposition strategy and with valid inequalities. Considering the initial solutions without decomposition or valid inequalities, in total 20 approaches are tried. We further improve these by applying Covering Cut Bundles (CCB). Details of these techniques are discussed in Appendix A.

6.2 A heuristic approach

Preliminary runs show that more than 90% of the total Benders running time is spent on solving the subproblem. To reduce this time, a two-phase approach is proposed. This method relies on alternating the "power" parameter in BPR function in (1). In the first phase, Bender's algorithm is employed under $\beta = 1$, while in the second phase, taking the binary variable values obtained by the end of the first phase as the initial solution of the (MP), the Benders algorithm is run this time taking $\beta = 2$. The algorithm is then iterated until convergence.

Since derived cuts in the first phase may lead to a non-optimal (MP) solution, the two-phase approach may converge to a non-optimal solution. In the following section, we present the performance of the heuristic.

6.3 Performance of the acceleration techniques and the heuristic

We test the proposed techniques under some well-known instances (https://github.com/bstabler/TransportationNetworks). The test instances are named as Sioux Falls, Berlin-Friedrichshain and Berlin-Mitte-Center (See Table 3 for specifics of the networks).

Table 3. Specifics of the test networks

Network	Network Size	# Nodes	$\lvert Z\rvert$	$\lvert A\rvert$	$\lvert H\rvert$	$\lvert J\rvert$	$\lvert P\rvert$	Total Demand
Sioux fall (S)	Small	24	76	9	8	7	0	12000
Berlin-Friedrichshain (BF)	Medium	224	531	45	94	30	50	35100
Berlin-Mitte-Center(BMC)	Large	398	871	65	113	40	180	55200

For each network, 16 instances are created by taking two levels for each of the four selected parameters, namely; time windows (*tw*) with values 60 and 80 for heavily injured and 80 and 120 for the moderately injured in both Berlin-Friedrichshain (BF) and Berlin-Mitte-Center (BMC) and values 5 and 15 for heavily injured and 15 and 30 for the moderately injured in Sioux fall (S), tolerance degree (λ) with values 0.4 and 0.8, maximum number of routes between each affected area-hospital pair (*ne*) with values 2 and 3, and maximum number of temporary hospitals (*n*) with values 4 and 7 for S network, 15 and 30 for BF, and 20 and 40 for BMC. The names of the test problems consist of five symbols, where the first four indicate levels of *tw,* λ*, ne,* and *n* (each taking value of 1 or 2). The final symbol represents the name of the network. For example, 1111BF corresponds to a test problem in the Berlin-Friedrichshain network where *tw,* λ*, n,* and *ne* are all at their first level.

The computational results are obtained using CPLEX 12.7.0 on a 2.80 GHz Intel i7 server with 32 GB RAM. The results indicate that selecting initial solution 1 or initial solution 3 as the warm start, combining it with auxiliary variables-based decomposition approach and not adding any valid inequalities yields the best combination of acceleration technique in terms of solution times for small-, medium- and large-sized problems. CCB is effective for medium- and large-sized instances, while not so much for small-sized instanced. Table 4 presents the runtime for the resolved test problems utilizing the suggested Benders decomposition, accelerated by the best combination of suggested warm start, decomposition and valid inequalities, along with CCB.

While for small sized networks there is no remarkable difference between the solutions obtained by CPLEX and Benders decomposition, for the medium and large-sized networks, the instances cannot be solved within a reasonable time using standard CPLEX solver. The findings reveal that when CPLEX solver is employed to solve the original model (without Benders decomposition), running time for the S network range from 157 to 1795 seconds, whereas for the BF and BMC networks, the running times exceed 5400 and 10800 seconds, respectively.

Table 4. Comparing solution times (in CPUs) of test problems designed for different networks

Instance name	**Benders decomposition (Best combination)**	**Benders decomposition Best combination & CCB**	**Instance name**	**Benders decomposition (Best combination)**	**Benders decomposition Best combination & CCB**
1121S	321	278	2121S	100	138
1122S	256	285	2122S	79	158
1111S	425	380	2111S	217	192
1112S	434	410	2112S	224	166
1221S	490	373	2221S	165	126
1222S	473	420	2222S	121	101
1211S	636	531	2211S	352	204
1211S	538	469	2212S	276	242
1121BF	1041	801	2121BF	1168	793
1122BF	1086	844	2122BF	1224	865
1111BF	1384	922	2111BF	1886	1438
1112BF	1420	1029	2112BF	1433	1010
1221BF	1338	989	2221BF	1698	1286
1222BF	1317	931	2222BF	1466	1147
1211BF	1746	1299	2211BF	2268	1607
1211BF	1536	1132	2212BF	2035	1538
1121BMC	1213	824	2121BMC	2284	1703
1122BMC	1197	727	2122BMC	2146	1638
1111BMC	1807	1339	2111BMC	2666	1857
1112BMC	1520	1111	2112BMC	2449	1702
1221BMC	2070	1669	2221BMC	2528	1739
1222BMC	1625	1300	2222BMC	2416	1651
1222BMC	2261	1555	2211BMC	2977	1945
1212BMC	1967	1454	2212BMC	2678	1838

The application of the heuristic approach in Benders decomposition, on average, results in a 73% reduction in solution time compared to the best combination of acceleration methods and CCB proposed in the suggested Benders decomposition. However, this improvement in solution time is accompanied by a 3% deterioration in the objective function when compared to Benders decomposition accelerated by the best combination of acceleration methods and CCB.

7. Application of the Methodology: İstanbul Case Study

We apply our proposed methodology to the anticipated İstanbul earthquake. Turkey is located at the intersection of multiple tectonic plates (Arabian, African, Eurasian and Anatolian). On February 6th, the country was shaken with twin Pazarcık and Elbistan earthquakes of magnitudes 7.7Mw and 7.6Mw, respectively, which affected 11 cities, causing over 50,000 deaths. Within 48 hours 77 field hospitals of varying sizes and capabilities were constructed. Earthquakes of such magnitude show the importance of preparing plans for disaster response. Istanbul is a city with high economic significance, a population density of over 15 million, and with high susceptibility to seismic hazard. Throughout the history, Istanbul has been affected by devasting earthquakes. After the $M_w = 7.6$ Gölcük earthquake in 1999, a major earthquake is expected on the Marmara Region of the North Anatolian Fault Line in the near future. This threat renders it necessary to devise a healthcare preparedness plan. In 2002, Istanbul Metropolitan Municipality and the Japanese International Cooperation Agency (JICA) collaborated for a report on risk analysis for the city. The report includes information on social and physical conditions of the study area, an analysis of seismic damage, the development of a comprehensive geographic database and recommendations for preventing and mitigating seismic disasters, most of which used in our case study analysis. The JICA report indicates that the European side is composed of two regions with respect to their hazard risk levels (Karaman and Erden, 2014). The city is divided to Anatolian and European sides separated by Boğaziçi strait while connected by multiple bridges. Once an earthquake hits, transportation between the two sides of the city may not be available due to infrastructural damage or bottleneck congestion. Thus, the injured people living on each side of Istanbul are to be assigned to local hospitals. In this regard, three separate networks are considered in our study: Anatolian (Asian) side, European side low-risk level and European side high-risk level.

In the following, we first describe how we set the parameter values. In JICA report, four scenarios have been defined for the anticipated Istanbul earthquake considering the magnitude of the earthquake and the length of the fault line. In our study, we utilize the most probable scenario (Model A in JICA report) and the worst case scenario (Model C in JICA report). We then present the solution times for all networks under each of the two scenarios. Finally, we provide insights for disaster healthcare provision.

7.1 Data generation and parameter settings

Network Construction

In the Anatolian and European networks, the nodes for affected areas are assumed to be located at the center of the districts. The districts with population above 10,000 are represented by two nodes (two sub-districts are formed). The representative nodes are located based on population density map of DEZIM report. Then, the final demand points are pinned on the map using Turkey ArcGIS Shapefile Map Layers.

Candidate locations for temporary hospitals are determined from a set of randomly selected state schools (listed on https://okul.com.tr/). The locations of the school nodes are identified with the help of Google Earth and converted to ArcGIS layer. List of three types of permanent hospitals including Public Hospitals, Education Research Hospitals and University Hospitals are taken from the web sites of the Ministry of Health (https://data.ibb.gov.tr/dataset) and located using Google Earth. To identify road junctions, ArcGIS is used, taking intersection of the arcs as a road junction.

To develop the road network, we use Google Earth (as of 2019) to identify the roads with a width of more than 16m. These are functioning as main roads (highways and large streets). Each route is composed of arcs from origin nodes (denoting districts) to destination nodes (hospitals). A route may cross the major road junction points in the network. A road junction is an intersection point where different routes meet. Table 5 details the characteristics of Anatolian and European networks, indicating the number of links (Z), affected areas (A), permanent hospitals (H), temporary hospitals (J), and junction points (P)

Table 5. Specifics of the three networks in Istanbul case study

Istanbul Network	**# Nodes**	$\lvert Z \rvert$	$\lvert A \rvert$	$\lvert H \rvert$	$\lvert J \rvert$	$\lvert P \rvert$
High risk European (EH)	139	390	9	20	39	71
Low risk European (EL)	222	565	12	27	42	141
Anatolian (AN)	207	568	7	22	36	142

The final maps of the networks are provided in Figures 1 and 2.

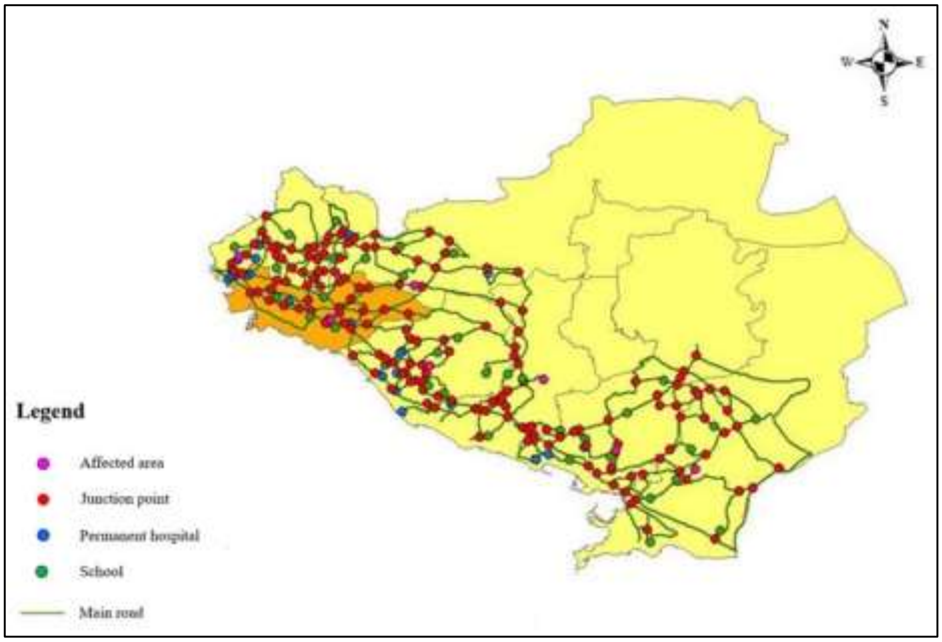

Figure 1. The network for the Anatolian side of Istanbul (via ArcMap)

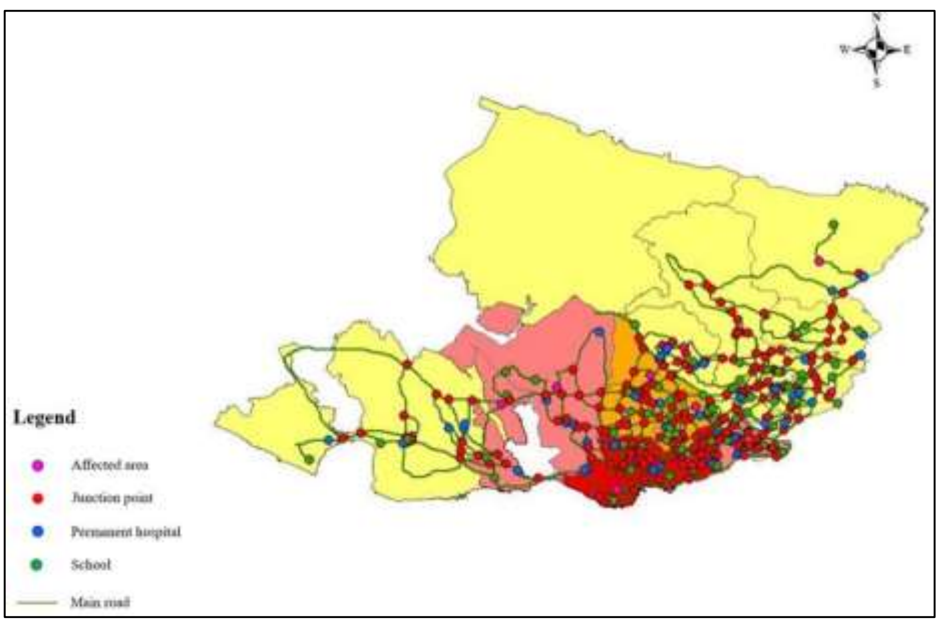

Figure 2. The network for the European side of Istanbul including areas

Routes

We generate Network dataset in Arc Catalog and use Network Analyst extension of ArcGIS to find connected nodes making arcs and calculate the length of them. Additionally, we generate eligible routes for each injury class under various values of tolerance degree (λ) and σ, in accordance with the specifications of time windows, vehicle velocity (*ve*) of 30km/hr (Acar and Kaya, 2019), and a coverage radius (*cvr*) of 15km. For the heavily injured and moderately injured, we have set the time-window lengths to 10 minutes and 30 minutes, respectively. For the European networks, the node structure of the network is dense, setting $\sigma = 1$ makes many hospital choices available for affected areas. For the European side test problems, σ is set to 1 and 2. For the Anatolian network, the nodes are sparsely located. Choice of $\sigma = 1$ makes the network disconnected, leaving no hospital choices for the affected areas. Therefore, σ is taken as 2 and 2.5 for different test problems of the Anatolian side. For each network, the number of routes between each pair (ne) is set as 2 and 3. The tolerance degree (λ) is set for each network so that significant variations in the number of feasible routes and accordingly in computational results are observed. For the High-risk area, λ is set to 0.1 and 0.15, while for the Low-risk area, it takes values of 0.25 and 0.4. For the Anatolian side, the tolerance degree is chosen as 0.15 and 0.2.

Arcs

Arcs connect two nodes in the network and multiple arcs form a route. To obtain the time required to traverse an arc under congestion (in BPR function), we determine the base travel time of arc z at zero volume (t_z^0), and the effective hourly capacity of arc z, c_z (as defined in Table 3). Here, t_z^0 is obtained by dividing the arc length with the vehicle velocity (30km/hr).

The effective hourly capacity of arc z, c_z, is obtained by multiplying the hourly base arc capacity ($cbase_z$) with the arc's survival probability (p_z). According to Kırıkçı (2012), $cbase_z$ is defined as the maximum number of cars that cross arc z per hour under free flow conditions, and is expressed as follows:

$$cbase_z = \left(\frac{rvs}{v}\right)^{-1} (cap_{rv}) \tag{51}$$

In (51), rvs is the spacing of two consecutive vehicles, taken as $15m$, v is the velocity of the ambulance taken as 30km/hr and cap_{rv} is the capacity of the ambulance taken as 1 injured person per trip (Acar&Kaya, 2019, Repoussis et al., 2016, Salman & Gul, 2014). Since the base capacity of an arc ($cbase_z$) is independent of its length, all the arcs in the network have the same $cbase_z$. In this case, $cbase_z$ is calculated to be 2000 based on the aforementioned parameters. ($\left(\frac{15m/car}{30000m/hr}\right)^{-1} 1\ injured/car = \quad 2000\ injured/hr$)

Disruption of road network

The earthquake may result in a decrease in the capacities of some of the arcs. Let p_z denote the probability that arc z is usable after the earthquake (Salman and Yucel, 2015):

$$p_z = 1 - \beta_z \, PGA_z \tag{52}$$

where β_z is a seismic zone factor based on where arc z is located. According to seismic intensity map (available in DEZIM report), there are four zones in Istanbul. Each zone is assigned a seismic zone factor ($\beta_z = 0.95$, if Zone 1, $\beta_z = 0.85$, if Zone 2, $\beta_z = 0.75$, if Zone 3, and $\beta_z = 0.65$, if Zone 4) to represent the expected damage risk in the event of an earthquake, with Zone 1 being the most risky. In (53), PGA_z is the peak ground acceleration at arc z, calculated as:

$$PGA_z = \gamma \frac{e^{0.8\mu}}{(r_z+40)^2} \tag{53}$$

where μ is the earthquake magnitude in Richter scale (that takes values 7.5 and 7.7 under scenarios A and C respectively) and r_z is the distance between the arc and the fault line. To calculate r_z, we measure the distance between the midpoint of the affected area where the arc is located and the fault line. In (53), the parameter γ is used to predefine the range of survival probability of arcs. To ensure a rational range of survival probability under scenario C, we set γ to 6.5, resulting in a reasonable range of [%8.4-%63].

Thus, resulting arc capacity is, $c_z = cbase_z . p_z$. We further assume that a certain percentage of the hourly base arc capacity is preoccupied by non-emergency vehicles, by a factor of oc_z. oc_z is determined with respect to the population and it is taken as 46%, 54%, 35% of $cbase_z$ for AN, EL and EH networks, respectively

Number of injured per period (np)

JICA report provides for each affected area a, the percentage of moderately injured and heavily injured people, $per_{a,1}, per_{a,2}$, with respect to the scenario under consideration. It is assumed in the report that 10% of injured people are heavily injured: $\frac{per_{a,1}}{per_{a,1}+per_{a,2}} = 10\%$, in each of the scenarios. For injury level $i = 1,2$, the base population of the area, $bpop_a$ (obtained from Turkish Statistical Institute, TUIK, https://www.tuik.gov.tr/Home/Index), multiplied with $per_{a,i}$ gives the cumulative number of injured at level i, $cumnp_{ai}$.

Our analysis assume that the planning horizon is divided into 1-hour periods with the carriage of the injured to the hospitals taking place periodically. The reason behind adopting a periodic approach is due to the limited number of available rescue forces and the extensive time required to identify all injured individuals, which cannot be done instantaneously. As a result, not all people will be prepared for evacuation simultaneously that prompts the consideration of a periodic approach. To determine the number of 1-hour periods in a planning horizon for each of the three regions, $\ell = 1,2,3$ (two European and one Anatolian), we assume that rescue rate of each region (rr_ℓ) is in accordance with the population of the region taking 0.038, 0.028, 0.019, respectively. For a given region ℓ, let T_ℓ denote the total number of periods (hours) required to transfer all injured. Then,

$$T_\ell = \frac{1}{rr_\ell} \tag{54}$$

For Anatolian, European-Low risk and European-high risk regions, T_ℓ is obtained as 26, 36 and 53, respectively. In network ℓ, the hourly number of injured for affected area a and injury level i is then, $np_{ai} = \frac{cumnp_{ai}}{T_\ell}$ (see also Table 3).

Capacity (service rate) of hospitals after the disruption to facilities (cap)

We specified the capacity of the hospitals based on number of available beds reported on (https://data.ibb.gov.tr/dataset). It is assumed that 50% of the capacity in the hospitals are already occupied. Furthermore, the capacity of hospitals decreases in relation to the damage ratio of buildings, as estimated in the JICA report (Oksuz and Satoglu, 2020). This report provides damage ratios for each district of Istanbul under scenarios A and C. Using the locations of hospitals, we calculated the corresponding reductions in hospital capacities. For example, if the percentage of damage to the buildings in an area under scenario C is 10%, then the capacity (service rate) of the hospitals in this area are decreased by 10% in the model.

Capacity of temporary hospitals, which are located at schools, are calculated according to their area (measured using Google Earth as of 2019) while assuming a standard temporary medical center (520 m^2) can serve 400 injured (or 1.3 m^2 space is required to treat any injured) (Oksuz & Satoglu, 2020).

Since heavily injured need to be hospitalized and wouldn't get discharged until the end of short term planning horizon (T_ℓ), the hospital capacity is divided by T_ℓ to obtain capacity per period, i.e., the *service rate.* The capacity per period for temporary hospitals are obtained in the same way.

Maximum number of temporary hospitals (n)

For high risk and low risk area of European side network, *n* is set as 25 and 30. In Anatolian side, n is set as 16 and 20.

7.2 Solution times for the Istanbul case study

To evaluate the performance of the proposed methods for Istanbul case under different scenarios and to investigate the effect of σ, λ, n and ne, 32 problems are designed for each of the Low-risk (EL) and High-risk (EH) European networks, as well as for the Anatolian network (A). Each problem has two levels of $n, ne, \sigma,$ and λ under scenario A and scenario C. It is assumed that time window (tw), coverage radius (cvr), hourly base arc capacity ($cbase_z$), are the same.

Table 6 presents the solution times for test problems for the Istanbul case study under scenarios A and C, using Benders decomposition method, accelerated with the best combination of the suggested techniques, including CCB as well as the performance of the heuristic.

In the table, name of the test problems is indicated in Section 6.3. In # of routes column, R_1 and R_2 represent the average number of routes in the network for heavily injured and moderately injured individuals, respectively, where both depend on σ and λ; however, in this column, the averages are calculated based on different values of λ. $|A - H|$ ($|A - H'|$) represents the total number of affected area-permanent (temporary) hospital pairs.

Table 6. Solution times (in CPUs) for designed test problems for the Istanbul networks under Bender's decomposition approach

Test problem	**Average number of routes**	**$\|A-H\|$ & $\|A-H'\|$**	**Scenario A**			**Scenario C**		
			Best combination	**CCB**	**Heuristic**	**Best**	**CCB**	**Heuristic**
111EH	R1:175 R2:7056 Max r1:8 Max r2:398	116 374	391	258	157	489	345	263
112EH			276	211	121	342	302	224
121EH			212	165	65	238	197	110
122EH			137	133	74	202	147	90
211EH	R1:955 R2:7056 Max r1:39 Max r2:398	243 374	935	605	400	1231	849	475
212EH			782	577	261	825	561	289
221EH			639	451	119	784	554	312
222EH			593	378	121	644	421	222
111EL	R1:70 R2:5127 Max r1:3 Maxr2:173	51 342	185	133	18	351	229	74
112EL			152	146	32	179	203	50
121EL			185	140	23	241	194	29
122EL			133	119	23	173	198	17
211EL	R1:748 R2:5127 Max r1:24 Max r2:173	197 342	590	430	147	1040	646	300
212EL			492	318	96	699	478	167
221EL			462	304	111	656	497	112
222EL			381	307	106	503	306	131
111A	R1:538 R2:3424 Max r1:23 Max r2:146	142 401	809	558	290	1057	655	467
112A			646	471	130	865	577	295
121A			436	344	188	706	486	297
122A			270	175	94	538	389	276
211A	R1:1711 R2:3424 Max r1:89	200 459	1428	1036	621	1691	1161	740
212A			944	701	434	1374	988	626
221A			934	695	335	1309	864	587

222A	Max r2:146		555	432	175	801	658	407

The study reveals that incorporating auxiliary variables into the master problem is generally beneficial, particularly for larger-sized problems in test networks. However, as network size and complexity increase, the master problem without lower bounds (LB) outperforms others, as LB does not consider congestion for complex problems, creating a notable gap between optimal solutions and LB. Specifically, for low complexity (σ=1) scenarios in European low-risk and high-risk areas, both fixed and iterated LB are effective. For higher complexities (σ>1), iterated LB is preferred in the European high-risk area, while the Anatolian side performs best without LB. In medium complexity for low-risk areas, iterated LB excels, but excluding LB is effective for other combinations of parameters. The study identifies a strong correlation between optimal initial solutions and the maximum number of routes between pairs in Istanbul networks. Initial solutions 1 and 3 are recommended for instances with small and large ne (number of routes), respectively, as removing redundant routes in solution 1 proves helpful in reducing solution time for more complicated cases. While the selection of acceleration techniques may not significantly be affected by λ (a parameter), it does impact solution time. Increasing λ results in more eligible routes and larger problem sizes, leading to longer solution times.

The computational time savings achieved by employing Benders decomposition algorithm (with acceleration techniques and CCB), in comparison to using commercial software (CPLEX) under scenario C is within [86%-98%] for the low risk European, [89%-98%] for the high risk European and [78%-96%] for the Anatolian networks. Note, for a given instance, the solution times under scenario C are higher than that of Scenario A. The difference stems from the fact that arc capacities are lower under Scenario C due to higher risk of damage. The heuristic approach leads to a reduction of 53% on the solution times beyond Benders decomposition approach on the average, while deteriorating the cost only by 4%. The solution times indicate that, if the model is run after the disaster takes place (once the damage level is better assessed), route selection and allocation decisions can be made in a responsive way.

7.3 Results and discussion

When evaluating the results, we consider the following performance measures:

1) Total cost (Eq. 1), and total cost of establishing temporary hospitals and transportation, violated capacity of permanent hospitals and violated time

2) Percentage of active permanent hospitals (%ACP): Let ACP denote the set of "active" permanent hospitals, i.e., $\sum_{i=1,2}\sum_{r\in R_{ji}} E_{ri} np_{a_r i} > 0, j \in H,$ with H being the set of all permanent hospitals.

$\%ACP = \frac{|ACP|}{|H|}$

3) Average capacity utilization of active permanent hospitals (UACP) and established temporary hospitals (UACT) ,

$UACP = \frac{\sum_{j \in ACP} \frac{\sum_{i=1,2} \sum_{r \in R_{ji}} E_{ri} np_{a_r i}}{cap_j}}{|ACP|}$, where ACP is the set of active permanent hospitals,

$UACT = \frac{\sum_{j \in ACT} \frac{\sum_{i=1,2} \sum_{r \in R_{ji}} E_{ri} np_{a_r i}}{cap_j}}{|ACT|}$, where ACT is the set of established temporary hospitals.

4) Maximum violated time for injury class i (V_i, see Eq. 31),

5) Average congestion ratio in the network: $\frac{\sum_{z \in Z} \frac{x_z}{c_z}}{|Z|}$

6) Gini index (G) as a measure of fairness. For a population of size n with measurements $\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{n}$ in ascending order,

$$G = \frac{2}{n} \cdot \frac{\sum_{i=1}^{n} i x_i}{\sum_{i=1}^{n} x_i} - \frac{n+1}{n} \tag{55}$$

We calculate the Gini index for transportation time of the two injury classes (GT_1, GT_2) and for distance travelled by the two injury classes (GD_1, GD_2). Note, a lower value of Gini index implies a fairer allocation.

We report the results for the optimal solution (which holistically considers congestion and fairness) and for the "myopic approach" where the decisions are made individually by each vehicle, non-altruistically ignoring other vehicles. Table 7a and 7b report the performance measures for both the optimal and the myopic solutions in Anatolian (AN), Low-risk European (EL), and High-risk European (EH) networks under scenarios A and C. Note AN, EL, and EH networks are in ascending order with respect to their size and complexity.

Table 7a. Performance measures of the test problems designed for Istanbul networks under Scenario A for optimal and myopic approach

Instance	**Solution approach**	**Total Cost**	V_1	V_2	**UACT**	**%ACP**	**UACP**	**Average congestion ratio**	GT_1	GT_2	GD_1	GD_2
11EH	Optimal	13299.6	0	0	64.1	85	1.2	1.57	0.39	0.29	0.41	0.36
11EH	Myopic	13299.6	0	0	64.1	85	1.2	1.74	0.39	0.29	0.41	0.34
22EH	Optimal	9305	0	0	76.92	55	1.1	1.57	0.33	0.32	0.34	0.38

22EH	Myopic	9305	0	0	76.92	55	1.1	1.74	0.33	0.34	0.34	0.35
21EH	Optimal	13299.6	0	0	64.1	85	1.2	1.57	0.39	0.29	0.41	0.36
21EH	Myopic	13299.6	0	0	64.1	85	1.2	1.74	0.39	0.29	0.41	0.34
12EH	Optimal	9425	0	1.32	76.9	55	1.14	1.58	0.33	0.35	0.34	0.39
12EH	Myopic	10408.82	0	7.67	71.79	50	1.34	1.74	0.33	0.4	0.34	0.37
11EL	Optimal	62578.5	0.05	7	59.5	77.7	4.72	1.274	0.24	0.34	0.29	0.32
11EL	Myopic	63173.53	9.3	22.9	59.52	37.03	5.9	1.35	0.3	0.43	0.28	0.29
22EL	Optimal	41824.6	0.07	7.09	71.42	74.07	1.4	1.276	0.36	0.37	0.37	0.33
22EL	Myopic	42433.46	19.94	22.9	64.28	25.92	3.4	1.35	0.41	0.45	0.31	0.31
21EL	Optimal	62576.8	0	7.09	59.5	77.7	4.72	1.274	0.24	0.35	0.29	0.32
21EL	Myopic	63110.52	9.6	22.9	59.52	37.03	5.2	1.35	0.33	0.44	0.29	0.29
12EL	Optimal	41754.2	0	7.09	71.42	77.7	1.24	1.274	0.33	0.37	0.4	0.34
12EL	Myopic	42219.38	20.1	22.9	66.66	25.92	2.61	1.35	0.45	0.49	0.34	0.33
11AN	Optimal	34904.3	0.65	1.85	44.4	77.2	0.95	1.005	0.32	0.4	0.55	0.4
11AN	Myopic	3516.8	14.5	7.2	44.4	45.4	2.5	1.041	0.2	0.28	0.04	0.19
22AN	Optimal	34027.3	0.65	2.68	55.5	18.1	1	1.005	0.17	0.23	0.06	0.31
22AN	Myopic	34704.81	20.1	7.2	47.22	31.8	1.3	1.041	0.41	0.46	0.36	0.29
21AN	Optimal	34904.3	0.65	1.85	44.4	77.2	0.95	1.005	0.32	0.4	0.55	0.4
21AN	Myopic	35416.8	14.5	7.2	44.4	45.4	2.5	1.041	0.2	0.28	0.04	0.19
12AN	Optimal	34027.2	0.65	2.63	55.5	18.1	1	1.005	0.17	0.23	0.06	0.31
12AN	Myopic	34704.81	20.1	7.2	47.22	31.8	1.3	1.041	0.41	0.46	0.36	0.29

Table 7b. Performance measures of the test problems designed for Istanbul networks under Scenario C for optimal and myopic approach

Instance	**Solution approach**	**Total Cost**	V_1	V_2	**UACT**	**%ACP**	**UACP**	**Average congestion ratio**	GT_1	GT_2	GD_1	GD_2
11EH	Optimal	28566	0	0	64.1	85	7.39	1.7	0.41	0.36	0.45	0.4
11EH	Myopic	28566	0	0	64.1	85	7.39	1.88	0.41	0.4	0.45	0.37
22EH	Optimal	11352.8	0	0	76.92	80	1.83	1.7	0.33	0.37	0.35	0.41
22EH	Myopic	11352.8	0	0	76.92	80	1.83	1.88	0.33	0.46	0.35	0.38
21EH	Optimal	28566	0	0	64.1	85	7.39	1.7	0.41	0.36	0.45	0.4
21EH	Myopic	28566	0	0	64.1	85	7.39	1.88	0.41	0.4	0.45	0.37
12EH	Optimal	11603.6	0	3.8	76.92	80	3.11	1.7	0.39	0.37	0.39	0.41
12EH	Myopic	12563.72	0	10.5	74.35	60	4.75	1.88	0.36	0.48	0.37	0.39
11EL	Optimal	107561.8	0	7.42	59.5	77.7	9.48	1.282	0.25	0.34	0.3	0.34
11EL	Myopic	108179.9	9.83	23.57	59.52	40.74	10.51	1.39	0.3	0.43	0.27	0.3
22EL	Optimal	83303.59	0.07	7.42	71.42	77.7	6.34	1.283	0.35	0.36	0.38	0.35
22EL	Myopic	83919.6	9.83	23.57	64.28	25.92	7.38	1.39	0.41	0.46	0.32	0.32
21EL	Optimal	107563.9	0.07	7.42	59.5	77.7	9.48	1.283	0.25	0.34	0.3	0.34
21EL	Myopic	108790.65	20.19	23.5	59.52	40.74	10.17	1.39	0.34	0.44	0.27	0.3
12EL	Optimal	83301.48	0	7.42	71.42	77.7	6.34	1.282	0.35	0.36	0.38	0.35
12EL	Myopic	84530.34	20.19	23.5	66.66	25.92	6.84	1.39	0.46	0.47	0.33	0.34
11AN	Optimal	59287.2	0.82	3.41	44.4	95	1.52	1.010	0.15	0.32	0.16	0.32
11AN	Myopic	59960.05	14.85	7.64	44.4	45.4	3.02	1.14	0.18	0.36	0.12	0.21
22AN	Optimal	43572.3	0.83	3.21	55.5	66	0.96	1.09	0.26	0.35	0.27	0.38
22AN	Myopic	44217.97	20.59	7.59	47.22	31.8	1.8	1.14	0.38	0.47	0.26	0.3
21AN	Optimal	59287.2	0.82	3.41	44.4	95	1.52	1.010	0.15	0.32	0.16	0.32
21AN	Myopic	59960.05	14.85	7.64	44.4	45.4	3.02	1.14	0.18	0.36	0.12	0.21
12AN	Optimal	43572.3	0.83	3.21	55.5	66	0.96	1.09	0.26	0.35	0.27	0.38
12AN	Myopic	44217.97	20.59	7.59	47.22	31.8	1.8	1.14	0.38	0.47	0.26	0.3

7.3.1 Results on congestion and transportation times

Computational results show that as the risk level in the network increases, the average congestion ratio increases, with the highest congestion ratio observed in EH. The reason is the majority of the arcs situated in the EH are under a high risk of damage, resulting in a reduced usable capacity. We further observe that in EH, although the preoccupied capacity of arcs (oc_z) is the smallest, the percentage of over-capacitated arcs is the highest (in EH the percentage is 75%, while for EL and AN it is around 50%). Although the average congestion ratio in EH is the highest, the maximum violated times (V_i) are mostly zero. This is because the EH network is concentrated within a small geographical area with short base travel times for feasible routes. Similarly, the maximum violation in the AN network is higher than that of EL since the base travel times in the AN network are significantly higher. Finally, we observe that V_i values do not change much across scenarios.

Due to the smaller population of heavily injured individuals, their stricter time window, and the higher penalties associated with time window violations, they arrive at medical centers sooner than moderately injured individuals. Additionally, the objective is to minimize the penalty cost for maximum violated time as part of the total cost, leading to efforts to keep travel times within the time window, particularly for heavily injured individuals who face higher penalties for time violations.

In all networks, myopic approach results in higher average congestion ratio than that of the systemic approach. In EH, EL and AN networks % increase in average congestion rate is 10.7%, 7.18% and 8.19%, respectively compared to the holistic (optimal)approach. We observe that the increase in congestion ratio (from holistic to myopic approach) is higher under scenario C compared to scenario A. The maximum violated times are higher under myopic approach, while the number of over-capacitated arcs is relatively smaller. This can be attributed to the smaller number of shortest routes with positive flow, which limits the impact on individual arcs.

This analysis reveals that while the myopic approach may simplify routing decisions by focusing on the nearest facilities, it consistently underperforms in managing congestion and adhering to time constraints. In contrast, the holistic approach more effectively balances network load and risk, leading to more reliable and efficient emergency response outcomes.

7.3.2. Results on cost

The EH network has lower establishment and transportation cost as well as lower penalty costs for time window violations compared to other networks, mainly due its dense nature. In line with expectations, the cost is higher under Scenario C compared to that under scenario A, since both transportation cost and penalties for time window violations and expanded permanent hospital capacity are higher due to higher number of injured and higher disaster impact on hospital infrastructure.

Since population of heavily injured is smaller and time window for them is tighter compared to moderately injured, they will be transported to closer hospitals resulting in smaller travel costs in contrast to moderately injured.

The myopic approach results in lower total distance traveled and thus the associated transportation cost is lower. However, total cost is higher due to larger violated times.

7.3.3 Results on utilization rate

We investigate the utilization rate of the permanent and temporary hospitals. The lowest UACP is observed in the AN network. This is because most of the permanent hospitals are located farther away from the affected areas, resulting in longer feasible routes compared to other networks. Results indicate that all temporary hospitals are active in all networks under all instances. This is due to their close proximity to the affected areas. The closest temporary hospitals are preferred over expanding the capacity of the permanent hospitals located at the same distance, since expanding the capacity is costlier.

Given the greater overall demand in scenario C, the utility rates for hospitals across all networks will consequently experience an increase in this scenario.

Because of a tighter time window for heavily injured cases and equal service levels in both permanent and temporary hospitals (with no priority given to hospital types), the preference is to choose the nearest hospital. Therefore, if permanent hospitals are closer than temporary ones, prioritizing the transfer of highly injured individuals to these permanent hospitals is crucial due to the limited capacity they have.

In the myopic approach, the UACP is higher for all networks than that of holistic approach. Since the injured are transferred to the closest hospitals via the shortest routes, in the myopic solution the %ACP is smaller than that of optimal solution, which makes UACP relatively higher.

7.3.4 Results on equitability

In the holistic approach, the least equitable assignment is observed in the EH network, with highest Gini indices for both time and distance. While the number of injured is higher in EH, the ratio of injured to available hospital capacity is smaller compared to AN and EL networks. Owing to the dense nature of the EH network, most injured are assigned to nearby hospitals, effectively meeting most of the demand. The remaining (constituting a small percentage of the total demand) are assigned to more distant hospitals due to capacity restrictions, resulting in high Gini indices for travel time and distance.

On average, the Gini index changes for the myopic approach are most significant in the high-risk area when comparing Scenario C to Scenario A. This is because the high-risk area has the highest level of risk, and there are more fluctuations in both demand and capacity of routes and hospitals. As a result, more noticeable changes occur in the myopic approach under Scenario C for the high-risk area.

In the myopic approach, it is observed that certain routes exhibit a significant amount of transportation time due to the presence of congested arcs along the routes. As a result, there is greater inequality in terms of travel times, leading to a larger $Gtime_i$ compared to the holistic solution. In contrast, optimal solution considers congestion on routes to the hospitals as part of the transportation planning, resulting in routes of varying lengths. Consequently, the dispersion of route lengths and $Gdist_i$ indices are larger compared to myopic solution.

In Figure 3, the dispersion of the travel times for each affected area are shown for the heavily injured, under holistic and myopic solutions (Scenario C of 2211AN). Note, for heavily injured only one of the available shortest routes is chosen, indicated by a single data point in the box plot. A similar plot for the moderately injured in Figure 4 indicates that the dispersion of travel times is higher than that of heavily injured. This is because the number of heavily injured is much lower and the time limit is tighter. Note that for both heavily and moderately injured, average travel times are higher under myopic solution than under holistic solution. we observe that when transporting the heavily injured in the myopic solution, time limits are violated for a high number of affected area-hospital pairs. For moderately injured, myopic solution does not result in violation of time limits (in almost all affected areas).

However, it is important to note that even when using the shortest routes and calculate the real travel time, there is still a high time violation for transferring a large volume of the injured to medical centers with limited capacity. Moreover, since the objective is to minimize the penalty cost for maximum violated time as part of the total cost, the travel time for most areas is kept within the time window, especially for heavily injured who face higher penalties for time violations

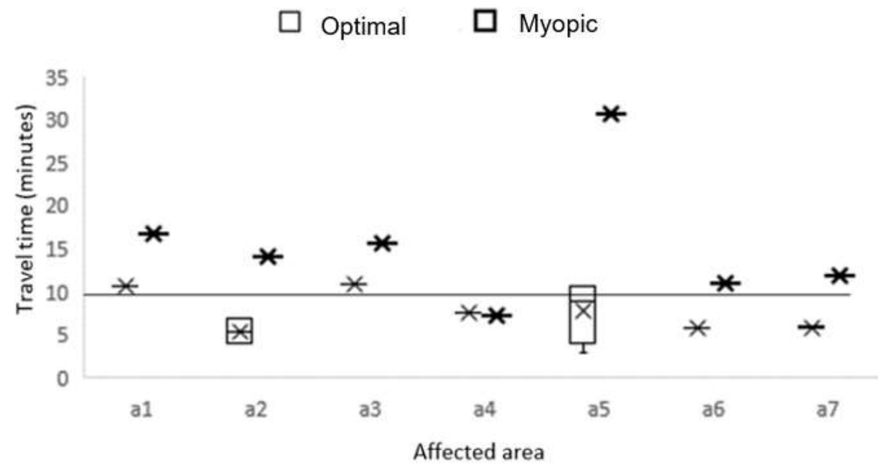

Figure 3. Box plot of travel time of selected optimal and shortest routes for heavily injured of different areas of problem 2211AN under scenario C

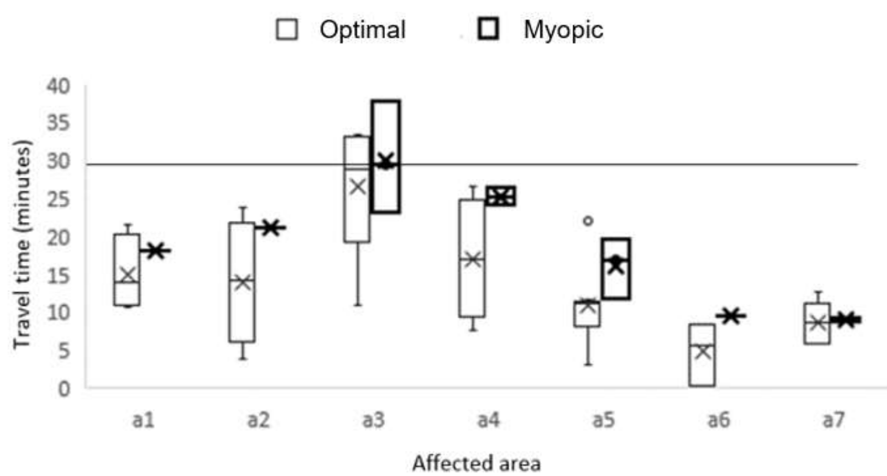

Figure 4. Box plot of travel time of selected optimal and shortest routes for moderately injured of different areas of problem 2211AN under scenario C

The scatter plot in Figure 5 illustrates how equitability and average value of transportation times are related for heavily and moderately injured, and how myopic solution affects the relation. According to the plot, there is a lower level of unfairness in terms of travel time for heavily injured compared to moderately injured.

Furthermore, under myopic solution the average transportation times are higher and transportation times are less equitable.

In Figure 5, the correlation between the Gini coefficient of travel time and average time is also evident.

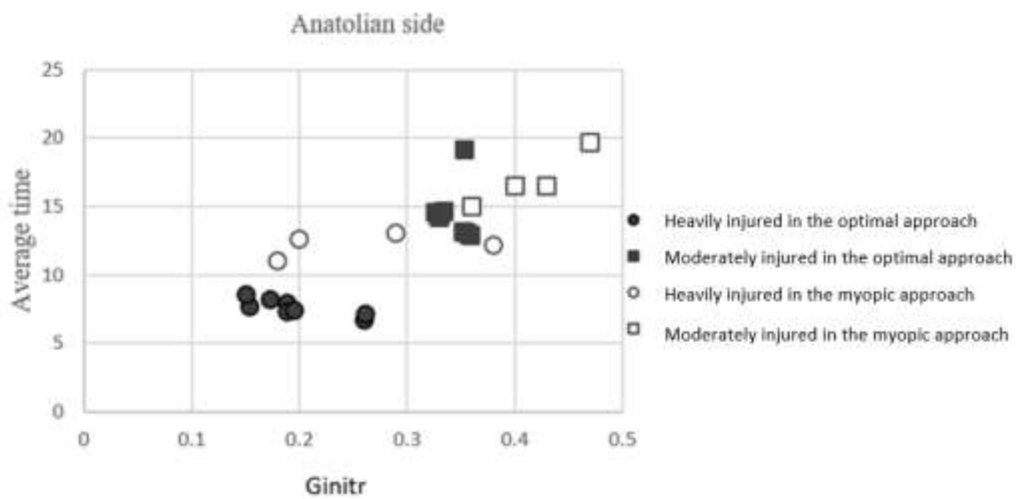

Figure 5. Gini coefficients (Gtime1 and Gtime 2) versus average travel time of heavily and moderately injured, under holistic and myopic solutions. (all instances of AN network under scenario C.

These findings underscore the critical importance of considering both equitability and efficiency in emergency evacuation planning. The holistic approach, by accounting for congestion and capacity constraints, demonstrates a more balanced distribution of travel times and distances, thereby ensuring that the network can function more equitably. Conversely, the myopic approach, while simpler, often results in significant differences, especially in high-risk areas where the demand is volatile and capacity is limited.

8. Conclusion and Future Research Directions

Our study focuses on developing a plan for efficiently aligning medical services with post-disaster emergency healthcare needs. A comprehensive model is proposed with decisions related to temporary hospital setup, capacity expansion, and casualty flow within a limited time. The model incorporates utilizes a BPR function for traffic flow on shared road segments, balancing drivers' preference for the shortest routes with overall transportation network efficiency. Uncertainties in medical evacuation demand and the capacity of routes and hospitals after earthquakes are considered through earthquake scenarios.

The model is applied to a real-world case study for a potential Istanbul earthquake, revealing the need for hospital capacity expansion and the establishment of temporary hospitals due to insufficient existing capacity. To address the complexity of the resulting MISOCP problem, the study employs an accelerated Benders decomposition algorithm, proving its significant time efficiency compared to an off-the-shelf solver. The proposed acceleration methods, including the use of auxiliary variables with fixed or iterated lower bounds and the CCB method under specific initial solutions, outperform other combinations in terms of runtime. The study also introduces a heuristic method that yields solutions with 4% (or 3%) optimality gap on the average. The impact of congestion is investigated by reformulating the model with a myopic approach, showing increased traffic congestion and associated penalties. The study suggests incorporating congestion in travel time calculations to enhance equity in casualty assignment and minimize delays.

The findings also reveal that extending the capacity of permanent hospitals may not be an optimal strategy, as it could result in congestion on the road network. Given the insufficient capacity of existing hospitals to serve all injured individuals, the establishment of temporary hospitals alongside permanent capacity extensions is necessary. This highlights the importance of a central planning approach to expand existing hospital capacities, establish new temporary hospitals, or arrange for the transportation of the injured to hospitals.

Future research directions include extending the model to a two-stage stochastic scenario-based approach, distinguishing between heavily and moderately injured individuals in their medical needs and services provided for them, and addressing situations where drivers deviate from suggested routes based on incomplete information. The study suggests considering additional decomposition-based methods for future research endeavors.

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