A hybrid robust optimization and simulation model to establish temporary emergency stations for earthquake relief

Sogol Mousavi [a], Seyed Mojtaba Sajadi [*b], Akbar Alem Tabriz [c], Seyyed Esmaeil Najafi [d]

[a, d] Industrial Engineering Department, Science and Research Branch, Islamic Azad University, Tehran, Iran,

Daneshgah Blvd, Simon Bulivar Blvd, Tehran, Iran, Postal Code: 1477893855,

Email: sogol.moosavi@yahoo.com, +989305439358, najafi1515@yahoo.com, +989124252899

[*b] Assistant Professor, School of Strategy and Leadership, Faculty of Business and Law, Coventry University, Coventry, UK CV1 5DL, Coventry University

Email: Mojtaba.Sajadi@Coventry.ac.uk, +44 (0)7594870606, (**Corresponding Author**)

[c] Department of Industrial Management, Management and Accounting Faculty, Shahid Beheshti University, Tehran, Iran,

Shahid Shahriari Square, Daneshjou Boulevard, Shahid Chamran Highway, Tehran, Iran, Post Code: 1983969411, Email: a-Tabriz@sbu.ic.ir, +989121578305

Abstract

Earthquakes pose a constant threat to human communities. A key step in improving preparedness against such disasters is to determine the optimal location of temporary emergency stations (TESs) and allocate them to affected areas. Decisions in the preparedness phase ensure optimal performance by TESs and minimize potential delays in rescue operations. During crises, TESs have a significant role in minimizing human causalities. In this research, a robust simulation-optimization approach is proposed to ensure appropriate planning in the preparedness phase. We develop a mathematical model for simultaneous and hierarchical location-allocation of the injured to the available medical facilities under disaster conditions. Since natural disasters are inherently unpredictable, the uncertainty of the data should inevitably be taken into account. We thus employ a robust optimization technique to tackle the uncertainty in the number of the injured and use simulation to create the first seven days of the crisis and determine the optimal capacities of medical facilities. The findings indicate that by eliminating the unnecessary transfer of mildly-injured victims to high-level medical facilities, the model causes a 15% reduction in treatment costs.

Keywords: Temporary emergency stations (TESs), Location-allocation, Simulation-based optimization, robust optimization method, Disaster Management.

1. Introduction

Natural disasters such as earthquakes, floods, landslides, volcanic eruptions, tsunami, etc. injure and kill thousands of humans each year and cause significant asset and habitat destruction [1]. Since the 1950s, the number and scope of disasters have been consistently on the rise. In particular, since the 1990s, an average of 235 million individuals per year have fallen victim to disasters. In 2014, 324 natural disasters were recorded worldwide, incurring a total of $99.2 billion in damages [2]. According to statistics from the International Disasters Database, Americas and Asia have dealt with the most intense earthquakes, landslides, floods, and typhoons in recent decades [3].

One of governments' most serious concerns is the increasing frequency of natural disasters and this underlines the necessity of enhancing nations' ability to withstand destructive events [4]. Since it is only a matter of time before the occurrence of the next natural disaster, governments and communities should have the necessary plans and measures firmly in place to minimize the potential destruction and casualties [5]. Proper planning and public awareness are widely believed to be effective at minimizing the scope of casualties and lost assets, which is essentially the central objective of response and rescue operations [6].

Given the increasing frequency of the disasters, researchers have recognized a vital need to efficiently assist the affected populations by placing greater emphasis on the theory and practice of disaster management (DM) [7]. Since emergency medical services (EMS) are in high demand in times of disaster, DM is classified into four stages to minimize the shock and prevent a state of chaos: mitigation, preparedness, response, and recovery. The first two phases are carried out pre-disaster, while the other two are reactive and conducted post-disaster [8]. In this regard, Rebeeh et al. [9] addressed DM theory and performance in industrial cities. The research encompasses all the stages of DM, with particular focus on modeling, support systems, resources, and facilities.

In the post-disaster phase, the existing hospitals and clinics cannot be expected to serve all the injured victims due to various technical difficulties and the overwhelming number of casualties [10]. Therefore, anticipating disasters and planning TESs in appropriate locations in disaster-prone cities could significantly mitigate the shortage of medical facilities.

The purpose of emergency facility-location (EFL) problems is to determine the optimal geographical location of new facilities to provide various emergency services to the affected populations in the aftermath of a disaster. Location-allocation problems are classified into two broad categories: regular and hierarchical. In systems with hierarchical facilities, there are multiple service levels available to the injured [11].

Since there is strong uncertainty in crisis situations, the model's uncertain parameters are analyzed through techniques of coping with uncertainty. Studies on healthcare systems often deal with many types of uncertain data, factors, and parameters. Stochastic programming, robust optimization, and simulation software have been some of the most widely-used tools by researchers to address and counter uncertainty. Ahmadi-Javid et al. [12] reviewed 220 research papers on this subject and concluded that few studies had worked on the uncertainty faced by temporary medical centers.

Iran is located on one of the most active seismic belts in the world, with numerous faults identified across the country. Consequently, earthquakes are a real possibility in the country. There are four major faults in Tehran which are feared to activate. Ahmadzadeh et al. [13]

assessed the response to the 2017 Kermanshah earthquake, the most recent major earthquake in Iran.

Given the necessity of pre-disaster planning, we propose a network of emergency healthcare facilities with hierarchical allocation. We first develop a robust bi-objective optimization model to determine the locations of TESs and allocate the injured to the nearest TES. In the second phase, the simulation model incorporates the uncertainty in the response and rescue operation, treatment of the injured, and accessibility of TESs. The model mainly simulates the behavior of the injured and the congestion forming in hospitals after an earthquake and helps determine the optimal capacity of the three types of medical facilities in the hierarchical structure. Both the mathematical and simulation models minimize the distance traveled and the cost of establishing TESs.

The contributions of this study to the literature are as follows:

- Location and allocation are done simultaneously;
- Demand is the key parameter in the mathematical model which is solved using robust optimization;
- A hybrid model (mathematical + simulation) is developed;
- The mathematical model features both direct and hierarchical allocation strategies;
- The model incorporates urban infrastructure parameters such as the Richter scale, urban quality building coefficient urban areas, etc.;
- Preparing backup TESs.

The remainder of this paper is organized as follows: Section 2 reviews the literature on EFL models. Section 3 presents the modeling assumptions and mathematical programming formulas. Section 4 introduces the solution method to determine the optimal locations and allocations using robust optimization and describes the process of simulating the onset of an earthquake. The computational results are detailed in Section 5. Finally, section 6 includes a brief conclusion and a number of recommendations for future research.

2. Literature Review

Selecting suitable locations for emergency facilities can increase the speed and efficiency of relief efforts and accelerate the response to disasters. EFL is considered a strategic decision. Prior research has often addressed deterministic and stochastic problems [14]. Most studies on deterministic problems have aimed to minimize transport costs, facility construction, and relief supply storage. In case of a crisis, the demand for medical assistance, casualties, response time, and scope of asset losses are uncertain [15]. Logistical strategies are various but all have the same objectives: maximizing coverage, minimizing the distance between affected areas and treatment centers, and selecting the most appropriate locations, all of which affect the process of identifying and prioritizing the decision criteria [16].

2.1. Relief logistic networks and emergency facility location

In the case of relief logistics networks, Beikia et al. [17] investigated an inverse logistical programming problem involving the response, recovery, and reconstruction phases after an earthquake using a case study. Ghasemi et al. [18] proposed a multi-objective stochastic programming model for evacuation and logistical supply distribution following an earthquake. Stage 1 decisions in the model concern the post-disaster phase, including the location of relief distribution centers and the quantity of stored relief supplies. Stage 2 decisions determine the optimal location of TMCs such that the process of treating the casualties and relief distribution is accelerated. Li et al. [19] examined the demand uncertainty caused by major disasters, proposing a cooperative maximal covering model and pointing to financial productivity and coverage of appeal as the criteria according to which humanitarian logistics performance should be evaluated. Khorsi et al. [20] worked on operational and logistical decisions in relief operations, including planning, routing, and resource allocation, using the ε-constraint and rolling horizon algorithms. Safaei et al. [21] developed an optimization model for logistical relief operations under disaster conditions by defining two sets of upper-echelon and lower-echelon objectives. Boonmee and Kasemset [22] addressed the location, inventory, and distribution of relief supplies during a crisis and developed a fuzzy model to minimize the response time and budget, and to determine storage locations, maximum stock in each storage, distribution management, and inventory holding. Fazli-Khalaf et al. [23] developed a multi-objective model to design an emergency blood supply chain (BSC) in the aftermath of a disaster with the goal of minimizing SC costs and delivery times between the facilities, as well as to maximize the reliability of lab tests performed on the blood received from donors. Due to the uncertainty of some input variables, two variations of the robust possibilistic ε-constraint method were used to solve the model. Naghipour and Bashiri [24] dealt with an emergency BSC with the goal of minimizing total supply chain cost in disaster situations and considered donors, blood transfusion centers, hospitals, and casualties, simultaneously.

Li et al. [25] reviewed the literature on facility-location and planning in emergency response with the emphasis on optimization methods and models. Liu et al. [26] developed a bi-objective mathematical model to maximize the projected survival rate, define a medical service allocation plan, and locating temporary medical centers by minimizing the operational costs of deploying ambulances and helicopters. Kumar et al. [27] developed a model to maximize demand coverage, paying attention to urban space details, urban infrastructure, and social elements such as internal compactness. Memari et al. [28] developed model for location-allocation of ambulances and helicopters with multiple paramedics. The first objective function (OF) minimized the costs of EMC response and the second OF minimized the treatment time of the injured. Baharmand et al. [29] proposed a multi-layer bi-objective location-allocation model for the consequences of natural disasters and used the augmented ε-constraint method v2. Chen et al. [30] designed a two-level programming model with multiple warehouses and damaged structures. Level 1 involves distribution and Level 2 focuses on repairing damaged roads. Verma and Gaukler [31] assessed a deterministic and a stochastic model to determine secure locations for emergency facilities.

2.2.Facility location models considering uncertainty

A common technique of tackling uncertainty, also adopted in our model, is robust optimization [32]. The approach is especially effective when there is insufficient information on probability distributions [33]. Given the uncertainty of DM, researchers have worked extensively on EFL. Alinaghian et al. [34] developed a robust mathematical model for location-allocation of medical facilities under normal and crisis conditions. The authors used the harmony search algorithm, tabu search technique, variable neighborhood search, and a lower bound to solve the problem using the Lagrangian method. Mamashli et al. [35] proposed an uncertain model for post-disaster conditions to minimize the cost, adverse social impact, environmental damage, and transportation risks, while maximizing the logistical system. Yu [36] developed a two-stage pre-disaster location model to improve preparedness. First, the warehouses are located and the emergency supplies are stored, then a robust stochastic optimization technique is employed to cope with the randomness of disaster-stricken areas and the disaster's severity. Tirkolaee et al. [37] proposed a robust mixed-integer linear model for allocation and scheduling of rescue units to minimize the weighted time of completing the emergency response operation and tardiness. Du et al. [38] introduced a three-stage mixed-integer linear optimization model to solve a HEL problem. The service levels increased over the three stages, with one rising from 88.53% to 96.44%.

Sun et al. [39] developed a robust optimization model to combine facility-location and the transfer of the injured. Finally, a robust optimization approach was adopted to counter uncertainty and create the robust equivalent of the proposed model. Ramezanian and Ghorbani [40] proposed a two-stage stochastic model to assist pre- and post-disaster decisions regarding the distribution of relief supplies to survivors. The model consisted of a scenario-based robust optimization approach to cope with demand uncertainty. Eshghi et al. [41] worked on a robust location-allocation and emergency response problem following a disaster, developing a mixed-integer nonlinear programming model to maximize equity and minimize total logistics costs. Sotoudeh-Anvari et al. [42] developed a stochastic model to allocate resources and search for people lost in disaster-stricken areas. A dynamic stochastic programming approach was employed to solve the problem. Velasquez et al. [43] proposed a two-stage stochastic optimization model to preposition relief supplies. First, the location and quantity of pre-disaster relief supplies are determined. Next, some emergency equipment is procured and distributed in the affected areas. Lastly, Makui et al. [44] produced a multi-objective model considering uncertainty in the number of casualties and transfer of the injured to healthcare facilities; a single-objective linear mathematical model for allocation and distribution of medical equipment from suppliers to healthcare facilities under emergency; and a hybrid two-stage model to minimize the total relief and rescue time and total cost, and maximize the extent to which the severity of injuries matched the specialty level of healthcare facilities.

Now, let us examine the applications of simulation in EFL and health network design. As a principle, longer waiting times in the emergency ward lowers the service level to patients, causes dissatisfaction, and in some cases, increases the mortality rate. Sepehri et al. [45] developed a simulation model with two scenarios to simulate the emergency ward during a disaster. Sajadi et al. [46] proposed a simulation-optimization algorithm to schedule the working hours of emergency ward nurses to reduce waiting times and increase overall satisfaction with the medical service in disaster conditions. Salehi et al. [47] developed a two-stage stochastic model to simulate the BSC in case of a possible earthquake in Tehran. The model was evaluated by Monte Carlo simulations. Gul et al. [48] proposed an integrated framework of artificial neural networks in five districts of Istanbul and used discrete-event simulation to enhance earthquake preparedness and estimate the number of casualties in emergency wards. Kamali et al. [49] minimized the response time to emergency requests by integrating optimization and simulation techniques, identifying several locations as suitable for setting up TESs based on indicators such as each district's population density and number of calls requesting assistance. Karatas and Yakıcı [50] investigated the effects of backup service level, demand assignment policy, demand density, number of facilities, and locations on the solution's performance, employing discrete-event simulation to assess the performance of the layout obtained from the deterministic model.

3. Problem definition and formulation

This study focuses on designing a hierarchical network of healthcare facilities that gets activated in case of a disaster. The goal is to minimize the distance traveled to transfer the injured to TESs and the total cost. A key aspect of this network is determining the optimal locations of TESs to minimize the post-disaster congestion at higher-level medical facilities i.e., clinics and hospitals. Figure 1 illustrates the structure of the research.

The diagram shows 30 urban districts. In calculating the distances between the areas, we use the center of each district. In our model, the intensity of the hypothetical earthquake is the same in all districts. Table 1 details the data.

3.1. Assumptions

The proposed model's underlying assumptions are as follows:

- The injured are classified based on triage assessment into three groups of mildly-, moderately-, and severely-injured victims.
- All victims are immediately transferred to the nearest TES first.
- Depending on the severity of the injury and distance to the nearest healthcare facility, some victims may be directly transferred to a clinic or hospital.
- Severely-injured victims are transferred directly to hospitals.
- A number of schools, mosques, and squares are selected as candidate locations to establish TESs.
- Three factors were considered in selecting the locations of TESs: resistance to potential damages, safe distance from potentially hazardous facilities, and adequate accessibility for vehicles.

In this subsection, we define the terms used in the mathematical model.

3.2.Sets and indices

i	areas
e	TESs
c	clinics

h	hospitals
$T\,(t_1,t_2,t_3)$	Triage

3.3.Parameter

d_{ch}	Distance between clinic c and hospital h
d_{ec}	Distance between TESs e and clinic c
d_{ie}	Distance between areas i and TESs e
$c\,\mathrm{ost}_e$	Set up cost TESs e
B	The Total budget for the construction of a TESs
P_i	Population of urban areas i
α_i	Damage coefficient of urban infrastructure i
r	Emergency severity coefficient
S_i	Urban quality building coefficient urban areas i
T_{it}	Percentage of emergency severity index t in urban areas i
P_{it}	The number of casualties in urban areas i in with emergency severity index t level
cap_h	capacity of hospital h
cap_e	capacity of TESs e
cap_c	capacity of clinic c
M	a very big number
β_C	the percent of casualties referred to Clinic c need more hospital-level services
β_e	the percent of casualties referred to TESs e need more hospital-level services
AC_h	The average cost of treatment for each casualty in the hospital h
AC_c	The average cost of treatment for each casualty in the Clinic c
AC_e	The average cost of treatment for each casualty in the TESs e

3.4.Variables

a_e	1, If the TESs is activated; and 0, otherwise.
x_{itech}	1, If the of casualties in urban area i with grade t severity index, first taken to e, then to c, and then to h; and 0, otherwise.
x_{ite}	1, If the of casualties in urban area i with grade t severity index, are transferred to e; and 0, otherwise.
x_{itec}	1, If the of casualties in urban area i with grade t severity index, are transferred to e then to c; and 0, otherwise.
y_{ite}	The number of casualties in urban area i with grade t severity index, are transferred to e
y_{itec}	The number of casualties in urban area i with grade t severity index, are transferred to e then to c
y_{iteh}	The number of casualties in urban area i with grade t severity index, are transferred to e then to c and then to h.
y_{itc}	The number of casualties in urban area i with grade t severity index, are transferred direct to c.
y_{iteh}	The number of casualties in urban area i with grade t severity index, are transferred direct to h.
D_{ite}	The number of casualties from the urban area i with the severity of index t have referred to the TESs e and are calling for services at the clinic level.
D_{itec}	The number of casualties from the urban area i with the severity of index t hav referred to the TESs e and are calling for services at the hospital level.

The number of casualties in urban district i with emergency severity index t level who have been affected by the Richter scale (r), considering the damage coefficient of urban infrastructure i (α_i) and urban quality building coefficient urban areas i (S_i) is obtained as follows:

$$P_{it} = P_i \times \alpha_i \times r \times (1 - S_i) \times T_{it} \tag{1}$$
$$0 \le S_i \le 1, \quad 0 \le r \le 1, \quad 0 \le \alpha_i \le 1$$

3.5.Mathematical model

$$\min z_1 = \sum_i \sum_t \sum_e \sum_c \sum_h d_{ch} \times y_{itech} + \sum_i \sum_t \sum_e \sum_c d_{ec} \times y_{itec} + \sum_i \sum_t \sum_e d_{ie} \times y_{ite} + \sum_i \sum_t \sum_c d_{ic} \times y_{itc} + \sum_i \sum_t \sum_h d_{th} \times y_{ith}$$

$$\min z_2 = \sum_a \mathrm{Cost}_e \times a_e + \sum_i \sum_t \sum_e \sum_c \sum_h AC_h \times y_{itech} + \sum_i \sum_t \sum_e \sum_c AC_c \times y_{itec} + \sum_i \sum_t \sum_e AC_e \times y_{ite} + \sum_i \sum_t \sum_c AC_c \times y_{itc} + \sum_i \sum_t \sum_h AC_h \times y_{ith} \tag{2}$$

$$\sum_e y_{ite} + \sum_c y_{itc} + \sum_h y_{ith} = P_{it} \qquad \forall i, t \tag{3}$$

$$y_{ite} \times \beta_e = D_{ite} \qquad \forall i, t, e \tag{4}$$

$$\sum_c y_{itec} = D_{ite} \qquad \forall i, t, e \tag{5}$$

$$y_{itec} \times \beta_c = D_{itec} \qquad \forall i, t, e, c \tag{6}$$

$$\sum_h y_{itech} = D_{itec} \qquad \forall i, t, e, c \tag{7}$$

$$y_{ite} \le M \times x_{ite} \qquad \forall i, t, e \tag{8}$$

$$y_{ite} \ge x_{ite} \qquad \forall i, t, e \tag{9}$$

$$y_{itec} \le M \times x_{itec} \qquad \forall i, t, e, c \tag{10}$$

$$y_{itec} \ge x_{itec} \qquad \forall i, t, e, c \tag{11}$$

$$y_{itech} \le M \times x_{itech} \qquad \forall i, t, e, c, h \tag{12}$$

$$y_{itech} \ge x_{itech} \qquad \forall i, t, e, c, h \tag{13}$$

$$x_{itec} \le x_{ite} \qquad \forall i, t, e, c \tag{14}$$

$$x_{itech} \le x_{itec} \qquad \forall i, t, e, c, h \tag{15}$$

$$x_{ite} \le a_e \qquad \forall i,t,e \tag{16}$$

$$\sum_i \sum_t \sum_e \sum_c y_{itech} + \sum_i \sum_t y_{ith} \le Cap_h \qquad \forall h \tag{17}$$

$$\sum_i \sum_t \sum_e y_{itec} + \sum_i \sum_t y_{itc} \le Cap_c \qquad \forall c \tag{18}$$

$$\sum_i \sum_t y_{ite} \le Cap_e \qquad \forall e \tag{19}$$

$$y_{ite}, y_{itec}, y_{itech}, y_{itc}, y_{ith}, D_{iec}, D_{ite} \ge 0 \tag{20}$$

$$x_{ite}, x_{itec}, x_{itech}, a_e \in \{0,1\} \tag{21}$$

Relation 2 expresses the OFs of the problem. OF 1 (Z1) states the distance traveled to transport the injured from disaster-stricken areas to TESs in the proposed hierarchical structure, and then from TESs to hospitals and/or clinics. The fourth and fifth expressions define the distance traveled to directly transfer some of the injured to hospitals and/or clinics in case the victims are either critically injured or very close to said healthcare facilities. Expression 1 in OF 2 (Z2) addresses the costs of establishing TESs and expressions 2-6 set the costs treating the injured. Specifically, expressions 2-4 address the costs of treating the injured individuals whom get transferred first to TESs and then to healthcare facilities, while expressions 5 and 6 involve victims whom get directly transferred from the affected areas to hospitals or clinics.

Relation 3 ensures all the injured individuals in the affected areas are transferred to a TES, clinic or hospital, and no victim remains unattended. Relation 4 expresses that a number of injured individuals visiting TESs are in such serious conditions that it is vital to transfer them to a clinic or hospital immediately. Variable D_{ite} is defined for such situations. Hence, $(1-\beta_e)$ refers to injured individuals who receive treatment at a TES and do not need to be transferred to a clinic or hospital. Relation 5 compels the model to respond to all the victims D_{ite} who attend TESs and need higher-level medical attention, ensuring their immediate transfer to an available clinic.

Relation 6 is the same as relation 5, except those hospitals replace the clinics. Thus, $(1-\beta_c)$ represents injured victims who receive treatment in a clinic and get discharged. Relation 7 allocates the victims discharged from clinics to the available hospitals D_{itec} . Relations 8 and 9 determine the link between the positive variable *a* and binary variable *b* in a way that when any value is assigned to variable *a*, variable *b* equals 1; otherwise, 0. Relations 10-13 determine the interaction of binary and positive variables.

Relations 14 and 15 connect variable *a* and variable *b* to make sure that the hierarchical structure of the problem remains intact. Relation 16 expresses that when a value is assigned to variable *a*, the TES is operational and the OF takes its establishment cost into account. Relations 17-19 determine each TESs capacity. Relations 20 and 21 define the type of each variable.

4. Solution Approach

The solution approach in this paper proceeds over two steps. First, demand uncertainty for injured victims who should be transferred from TESs to a clinic and hospital during the crisis is obtained by robust optimization. In the second step, the simulation model is used for the other uncertain parameters, including the rescue operation, treatment and transfer of the injured, availability of TESs and optimal capacity of the healthcare facilities.

4.1.Robust optimization model

Robust optimization (RO) is one of several techniques of dealing with uncertainty. RO searches for near-optimal solutions to maintain their feasibility. Bertsimas and Sim [51] introduced an efficient approach based on linear distance to control the level of conservatism in solutions under uncertainty. The model proposed in this research is developed based on Bertsimas and Sim's approach with the objective of coping with demand uncertainty. In this study, only parameter P_{it} is considered uncertain. As a result, only constraint 3 in the mathematical model is formulated using Bertsimas and Sim's approach. The mathematical model obtained here is a mixed-integer linear programming model.

Robustness variables:

Z_{it}

r_{it}

Modified variables:

$$\sum_{e} y_{ite} + \sum_{c} y_{itc} + \sum_{h} y_{ith} \geq P_{it} + Z_{it} + \Gamma_{it} + r_{it} \qquad \forall i,t \tag{22}$$

$$Z_{it} + r_{it} \geq P_{it} \qquad \forall i,t \tag{23}$$

$$Z_{it}, r_{it} \geq 0 \tag{24}$$

4.2.Simulation model

We use Arena v14 to perform the simulations. In this section, we use simulation to describe the behavior of the injured and the system's performance in case of a disaster. The simulation model considers uncertainty in three areas: response and rescue operation, treatment and transfer of the injured, and availability of TESs. The other objective of the model is to determine the optimal capacity of each healthcare facility in the three-layer hierarchical structure.

The simulation model aims to reduce the cost of providing hospital beds and the injured victims' waiting times. Lastly, the simulation model only covers the first 7 days (168hr) of the crisis. In the second part, the optimization-based simulation is performed with to determine the optimal capacity of the service provided to the injured in a hypothetical crisis to achieve maximum coverage in the targeted districts. In this section, the cost is optimized and the average waiting time is minimized. Thus, we use OptQuest to test various time and cost combinations.

5. Computational results

In this section, the validity of the main model is examined through some numerical examples. After solving the model using robust optimization in the modeling software GAMS v24., the pareto-optimal solution obtained per each protection level (ta = 0, 1, 2, 3) based on Table 2 are reported in Figure 2. Higher values of the protection level (an uncertain parameter) indicate a more pessimistic state and thereby a higher cost of establishing TESs.

In this study, the protection level is realistic (ta=0). Thus, the most suitable candidate locations were selected for the establishment of TESs, with five stations remaining inactive on stand-by mode. Next, the structure for the allocation and transfer of the injured, both directly and hierarchically, from the 30 urban districts to the designated healthcare facilities was determined.

The allocation method adopted in the rest of the urban districts are detailed in Figure 3.

The values of the OF obtained from solving the first phase of the simulation model are listed in Table 3.

As can be seen, the estimated interval for the average OF is $[559303 \pm 2567]$ i.e $[556736\ ,\ 561870]$. The OF is equal to the weighted sum of the costs of establishing TESs, treatment costs, and waiting times. The results of the optimization model, obtained from Opt Quest, are as follows in Figure 4.

The optimal value of the OF is reported in Table 4. The results indicate that the OF has improved by 35%.

In the end, the optimal capacities of TESs are obtained using simulation-based optimization. The results reveal a 15% reduction in costs because the injured individuals whom can be treated in lower-level healthcare facilities are no longer unnecessarily transferred to higher-level, overqualified healthcare facilities. Table 5 compares the values of the objective function before and after optimization.

6. Conclusion and future research

In this study, we proposed an integrated DM model that is a combination of a mathematical programming model and a simulation-based optimization model. We first investigated the location-allocation of TESs to minimize the total cost and distance traveled. In the mathematical model, the injured victims are transferred to healthcare facilities both hierarchically (first to TESs, then to clinics or hospitals if necessary) and directly (to clinics or hospitals). Because of the uncertainty in the number of disaster-stricken people, we also solved the mathematical model using robust optimization in order to obtain pareto-optimal solutions. In the second stage, the output of the mathematical model is used as the input of the simulation-based model. A number of uncertain parameters are introduced to make the model more applicable under real-world conditions. In the end, the simulation-based optimization approach determines the optimal capacity of TESs. The results indicate that preventing the unnecessary transfer of mildly-injured patients to high-level facilities results in a 15% reduction in treatment costs.

For future research, it is recommended that location, allocation and storage of relief supplies under disaster conditions be added to the model developed in this study. The problem may also be solved at large scales using metaheuristics and the results can be compared. Since natural disasters often damage roads and significantly hamper rescue and relief efforts on the ground, it may be useful to consider aerial routing and relief systems in similar problems and models.

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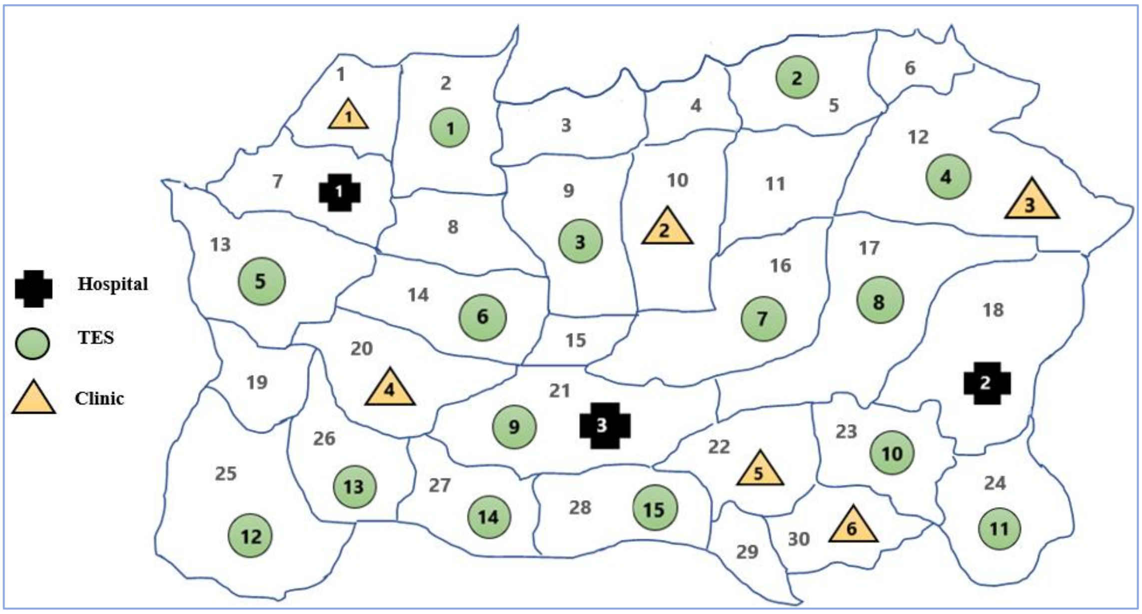

Figure 1. Dispersion of urban districts, TESs, clinics and hospitals

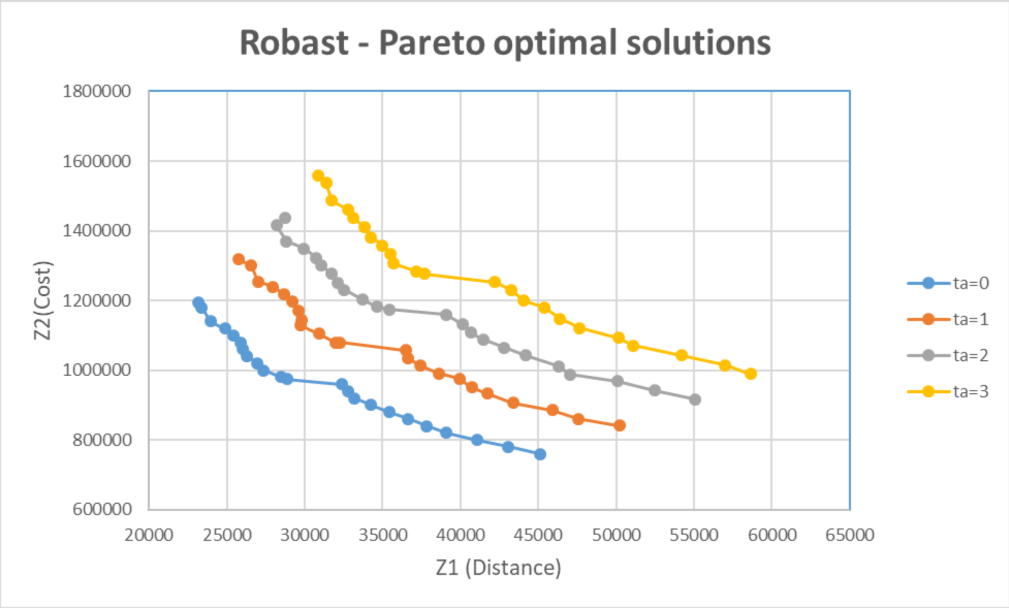

Figure 2. Pareto diagram of solutions

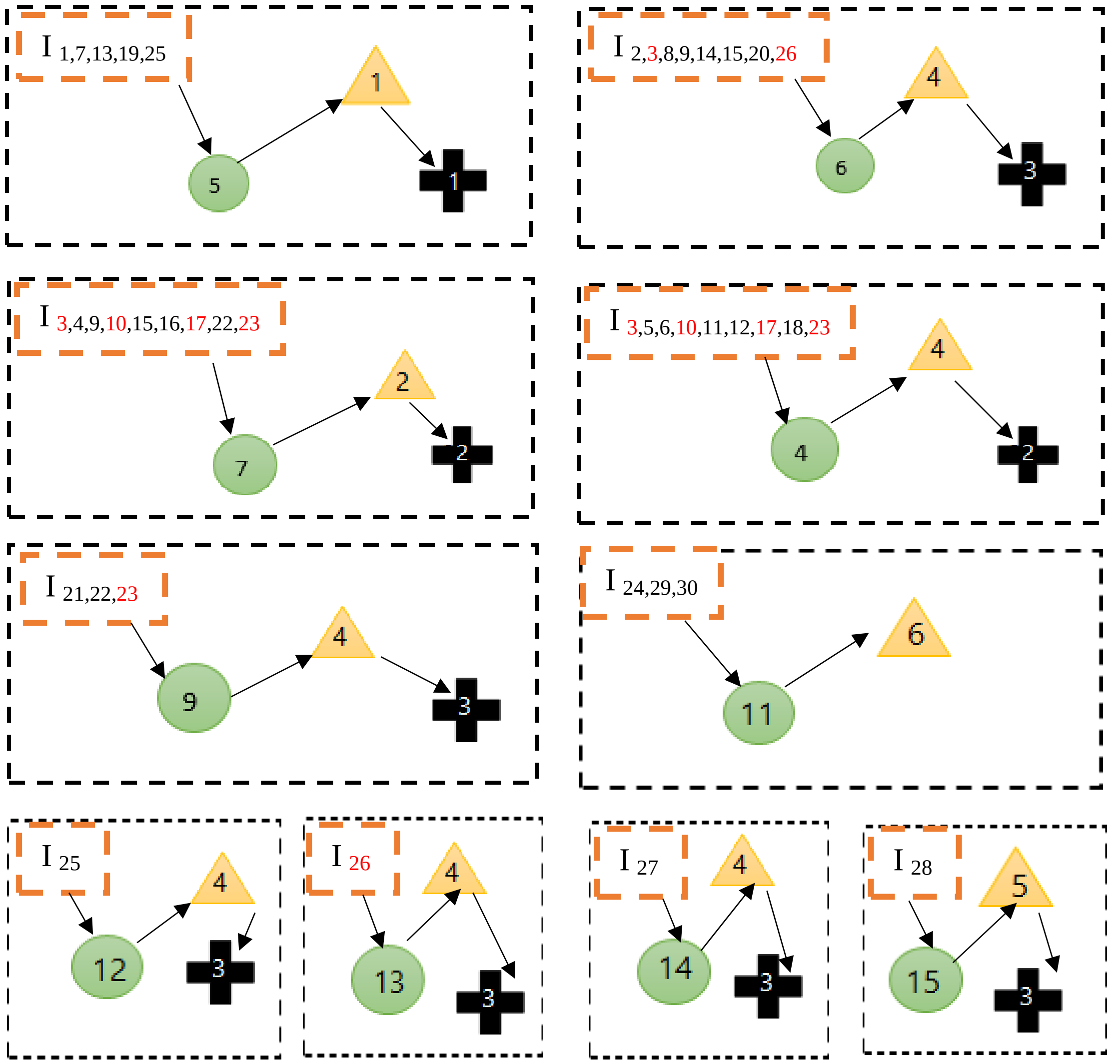

Figure 3. Allocation of urban districts to TESs, clinics and hospitals

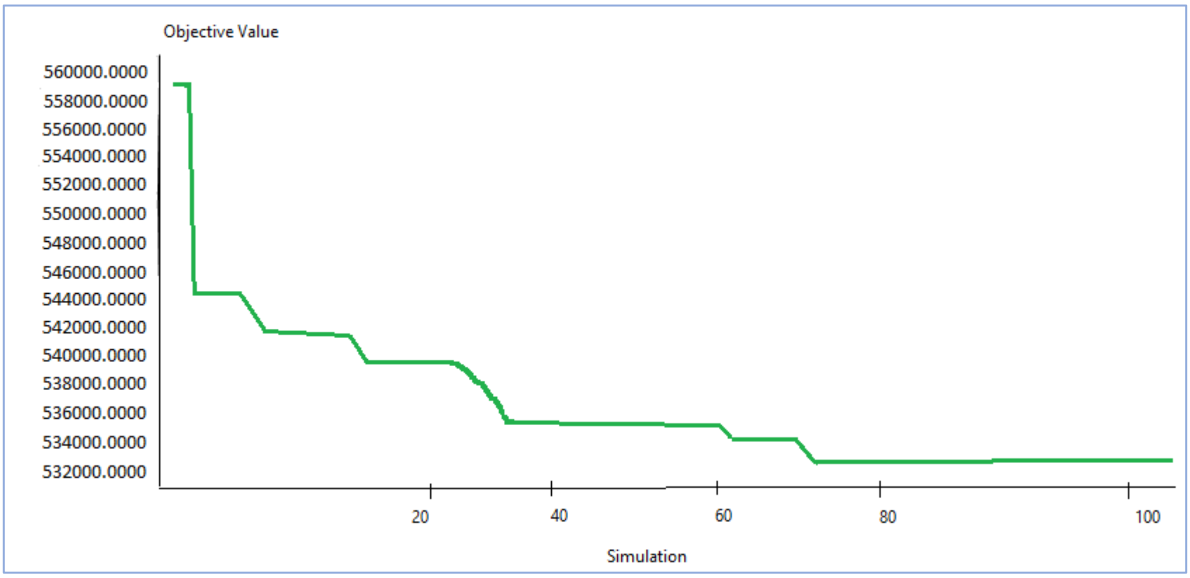

Figure 4. Reduction in value of the OF in simulation-based optimization

Table 1. Population of urban districts

Urban districts	Urban population	Areas	Damage Coefficient	Hospitals	Clinics	TESs
Northern	20000	12	0.01	1	3	4
Central	40000	7	0.04	1	1	5
Southern	60000	11	0.08	1	2	6

Table 2. Solutions obtained from robust optimization

Z1				Z2			
ta=0	**ta=1**	**ta=2**	**ta=3**	**ta=0**	**ta=1**	**ta=2**	**ta=3**
23205	25765	28712	30854	1195324	1317642	1437095	1557117
23396	26581	28209	31386	1180000	1300670	1416246	1537310
23941	27001	28825	31732	1140000	1254168	1369783	1487162
24887	27985	29954	32813	1120000	1238885	1349207	1459512
25438	28706	30753	33116	1100000	1217393	1322303	1437898
25872	29200	31058	33866	1080000	1196281	1301132	1409562
26003	29594	31761	34254	1060000	1170399	1275854	1381292
26295	29827	32118	34984	1040000	1144666	1249091	1357565
26972	29765	32556	35483	1020000	1128355	1230442	1334720
27375	30925	33743	35727	1000000	1104275	1202286	1305762
28484	31964	34679	37151	980000	1079770	1181631	1283076
28850	32274	35429	37727	975000	1080179	1173714	1275669
32420	36503	39089	42229	960000	1057909	1159480	1251976
32820	36620	40184	43258	940000	1034841	1131588	1231075
33220	37462	40670	44085	920000	1012499	1106899	1198965

34260	38620	41474	45371	900000	990814	1088661	1179876
35460	39927	42824	46400	880000	976083	1065316	1147664
36660	40730	44214	47678	860000	950007	1041826	1121336
37860	41769	46301	50157	840000	933228	1011902	1092657
39100	43401	47025	51107	820000	906022	988331	1071295
41100	45904	50110	54213	800000	885977	968841	1042310
43100	47550	52503	57023	780000	859928	942074	1014674
45100	50220	55065	58637	760000	840782	915853	988921

Table 3. Value of the OF in simulation

Expression	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
(OF)	559303.34	2567.16	555479.93	565945.54	555479.93	565945.54

Table 4. Value of the OF after optimization by OptQuest

Expression	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
(OF)	534125.71	2500.48	526941.42	537054.89	526941.42	537054.89

Table 5. Comparison of pre- and post-optimization values of the OF

Value of OFs before optimization	**[556736,561870]**
Optimal capacity of healthcare facilities	**783293**
Value of OFs after optimization	**[531625,536625]**
Optimal capacity of healthcare facilities	**532880**

Authors Biography

Seyed Mojtaba Sajadi received his BA in Industrial Engineering, Industrial Production, from Sharif University of Technology, MS in Industrial Engineering from University of Tehran, and Ph.D. in Industrial Engineering and Systems Management from AmirKabir University of Technology. His research interests include Business Analytics, Data Science, Operation Research, Simulation-Based Optimization, Design of Experiments, Mehta-heuristic Algorithms, Production Planning, Supply Chain Management and Healthcare.

Sogol Mousavi received her BA in Computer Engineering, Software. She completed her MS and Ph.D. degree in Industrial Engineering. She is a lecturer of industrial engineering of science and research branch of Islamic Azad University of Tehran. Her current research interests include Applied Operation Research, Simulation Optimization, Health care and

Disaster Management methods. She has published some research papers in International Journals and Conferences.

Akbar Alem Tabriz is a Professor in the Management and Accounting Faculty at Shahid Beheshti University, Tehran, Iran. He received his PhD in Management from Gazi University, Ankara, Turkey, in 1989. Most of his recent studies have focused on decision making, multi-objective optimization under uncertainty, and supply chain management.

Seyyed Esmaeil Najafi is associate professors of industrial engineering of science and research branch of Islamic Azad University of Tehran. His research interests are Industrial Engineering, Applied and Computational Mathematics, Operations Management, Optimization. Some of his publications are available from https://www.researchgate.net/profile/Esmaeil_Najafi3.