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RESEARCH PAPER

Dynamic Allocation Strategies for Medical Teams in the First Hours After Mass Casualty Incidents

Atefe Baghaian[1*], Hasan Rasay[2]

[1] *Esfarayen University of Technology, North Khorasan, Iran.*
[2] *Kermanshah University of Technology, Kermanshah, Iran.*

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Abstract

Due to the increase in the number and severity of disasters, managing the injured people immediately after a sudden-onset disaster is essential when there are limited resources, such as search and rescue and medical teams. These people are classified into the four triage groups. Uncertainty is an inevitable element in the chaotic environment after the disaster. This paper develops a robust stochastic optimization model to allocate the limited resources to the affected sites and casualty groups in the early aftermath of sudden-onset mass casualty incidents. Search and rescue operations and temporary treatment are considered in the model. Link disruption and facility unavailability in a dynamic environment are considered to make the model realistic. The robust model tries to maintain the optimal solution under given scenarios that are close to its expected value. We incorporate model and solution robustness in the model simultaneously. Numerical analysis experiments on the model performance, and the results are presented.

Keywords:
Sudden-onset disaster,
Robust stochastic,
Temporary treatment,
Resource allocation.

Introduction

The number and severity of natural and man-made disasters have generally increased in the recent two decades globally. (CRED, 2018) reports that 1.3 million people died and 4.4 billion people were affected by natural disasters from 1998 to 2017. The earthquake in Thailand in 2004, the earthquake in Haiti in 2010, and the cyclone Nargis in Myanmar in 2008 are the first three deadliest natural disasters from 1980 to 2017.

The disaster management cycle is comprised of four phases: mitigation, preparedness, response, and recovery. Casualty management is one of the several operations in the response phase that needs more attention due to its direct impact on the number of survivors. It includes five activities: resource dispatching and search and rescue, on-site triage, on-site assistance, transport to hospital, and comprehensive treatment in hospitals. This research focuses on the first three activities in casualty management to obtain an optimal location of casualty treatment stations (CTSs) and allocate relief teams to affected sites in the first hours after disasters.

The first hours after a disaster are very crucial in the casualty management phase. For example, 94% of people were rescued during the first 24 hours after the earthquake in Italy in 1980 (McGuigan, 2002). In the 1976 earthquake in Tangshan, China, 81% of the affected people were rescued on the first day, while it declined to 7.4% on the fifth day (Olson & Olson, 1987). On the other hand, in the earthquake 2010 in Haiti, poor infrastructure, the government's low response capacity, and the delay of the rescue teams had devastating effects on the country.

[*] Corresponding author: (A. Baghaian)
Email: a.baghaeyan@esfarayen.ac.ir

The lack of proper organization of search and rescue operations in the first critical hours after the 2003 earthquake in Bam, Iran, increased the number of fatalities (Ibrion et al., 2015).

As mentioned above, the importance of the casualty management is clear. There are a lot of people needing help and a few resources to help them in the first hours after a disaster. This issue has created motivation to answer the main questions of how the relief teams should be allocated to affected sites and how the casualties are dedicated to and treated at CTSs. The allocation of relief teams to affected sites is necessary to manage casualties efficiently. In this research, considering this issue, a mathematical model is developed for the optimal location of CTSs and also the optimal deployment of relief teams.

The paper is organized as follows. In Section 2, the literature is reviewed. Section 3 describes the mathematical models. In Section 4, the solution algorithm is explained. Section 5 is devoted to the experimental results. In Section 6, we present the conclusion and some directions for future research.

Literature Review

Casualty management is a challenging operation immediately after the disaster. Usually, the resources are very limited and the number of people who need help is very large. In this circumstance, managing the casualties needs proper planning. (Farahani et al., 2023) provide a comprehensive survey of publications between 1977 and 2019 on casualty management. They group the papers into five categories: resource dispatching (i) Resource dispatching/search and rescue, (ii) on-site triage, (iii) on-site medical assistance, (iv) transportation to hospitals, and (v) triage and comprehensive treatment. The category of the paper, key decision variables, main assumption, parameters, main constraints, objective function, solution approach, and the case study are specified for each paper in detail. After each category, the critical discussion is presented, and finally, the gaps, trends, and the extent of studies are suggested. Hence, the focus of this section is on the articles published after 2019 that are closely relevant to our research. Casualty management includes some activities such as rescuing the victims, triage in the field of the incident, medical assistance, transportation to the hospital, and treatment. We consider the studies related to these subjects, excluding the last one.

(Li et al., 2020) consider minimizing the total cost, transportation, and allocation cost in a three-stage robust and stochastic model for relief resource allocation and casualty evacuation. They used Lagrangian relaxation to solve the problem. (Gharib et al., 2021) developed a deterministic model to distribute emergency vehicles to the casualties and transport them to the hospital after the disaster in an urban emergency medical service, minimizing the waiting time for casualties and the total transport cost. They applied the ε-constraint method to solve the model. (Ghasemi et al., 2020) establish a stochastic model for logistic distribution and evacuation with three objective functions related to humanitarian and cost issues. An epsilon-constraint approach and genetic algorithm are implemented to solve the model. (Wang & Paul, 2020) proposed an adaptive robust optimization method to control the budget parameters and proved that their method could provide greater cost savings in hurricane preparedness. The case study verifies this method can contribute to greater cost savings in hurricane preparedness.

(Sun et al., 2021) address the problem of facility location and casualty transportation to minimize the injury severity score of casualties in two groups, mild and serious. (Baghaian et al., 2022) propose some strategies for relief teams' allocation to maximize the number of survivors. Also, (Rezapour et al., 2022) developed a strategy for casualty treatment with the same objective function. (Chang et al., 2023) study the problem of casualty collection point locations and resource allocation after the disaster to minimize the expected complete delivery time of casualties to hospitals. A heuristic algorithm is proposed to solve the problem efficiently.

In this paper, a robust stochastic mathematical model is presented to simultaneously optimize the dispatching of relief teams to the affected sites, allocate the casualties to CTSs, and assign the medical teams to casualty groups. The model copes with the infeasibility issues that may occur in

stochastic optimization problems. This approach returns the solutions that are close to any given scenario with minimum dispersion from the optimal values.

Problem Description

Providing medical services for too many casualties in the first hours after a disaster is a challenging issue. Consider an urban area that has severely been influenced by a sudden-onset Mass Casualty Incident (MCI) like an earthquake. Different sites containing buildings, public infrastructures, and properties may be affected and some connecting links in the transportation network may be damaged. Due to the high population density, there might also be a huge number of seriously injured people trapped in different buildings. Trapped people should be extricated and medically stabilized immediately. Therefore, Search-And-Rescue (SAR) as well as medical teams need to be dispatched to the affected sites to provide relief operations in permanent or temporary facilities. Temporary medical centers are required to be established to treat the victims on the field because there are a large number of injured people and some permanent medical centers/hospitals are damaged. Therefore, key decisions such as the allocation of relief teams to affected sites and the distribution of casualties to medical centers are to be made.

The casualty management in the response phase of a disaster is for saving lives which necessitates urgent actions in chaotic conditions after the incident. It is usually divided into two phases: (1) a first response and (2) a middle-term response. The former is to the rescue and first-aid medical assistance of the affected people, and the latter is to estimate and mitigate the potentially unattended first needs of the affected population as a result of possible damage to the life-line infrastructures and resources (Ortuño et al., 2013). We focus on the early 12 hours after a disaster with extremely limited relief resources which play an important role in saving human lives. An efficient resource allocation leads to an effective response to the incident. The time scope is divided into several discrete periods of equal lengths. As usual, the decisions are made at the beginning of each period and remain fixed during the period. The length of periods is assumed to be small enough to allow us to consider the dynamics of the problem.

Uncertainty is an inevitable element in the chaotic environment after a sudden-onset MCI. The post-disaster decisions usually include uncertainty coming from the lack of information or some inherent ambiguity. (Liberatore et al., 2013) discussed different uncertainties in both the demand and supply sides of humanitarian logistics. Demand side parameters, like the number of affected people, the availability of relief network routes, and the number of casualties to be positioned in triage groups, are unknown. Supply-side parameters rely basically on the capacity of known local relief teams with sufficient certainty in the first hours after the disaster. However, the flow of volunteers and relief teams from other regions changes the number of existing teams and makes it dynamic.

There are some approaches to handle the uncertainty of input parameters such as stochastic programming, fuzzy theory, and robust optimization. Some papers in this area considered stochastic optimization applying probability distributions of the uncertain parameters (Shishebori & Yousefi Babadi, 2015); however, there is very little primary data to estimate the probability distribution of parameters in an early response even on valid worldwide databases such as CRED, EM-DAT, and WHO. On the other hand, the historical data is not valid for other disasters with different magnitude, location, and time occurrence. Fuzzy theory is also used to handle uncertain parameters utilizing the knowledge of field experts and incomplete available data. These methods are capable of adjusting the satisfaction level of uncertain parameters based on the opinion of decision-makers (Pishvaee et al., 2011). They do not guarantee the optimization of satisfaction levels and the reliability of output results (Hamidieh et al., 2017). Optimization of satisfaction levels and the reliability of output results are not guaranteed in these approaches.

The uncertainty in the proposed model is handled by a scenario-based robust approach. When there are discrete uncertain parameters such as the number of casualties, the scenarios are defined by the different possible values with corresponding probabilities. The difficulty of predicting the timing and magnitude of a disaster makes it almost impossible to estimate the damage to human lives and infrastructures ((Barbarosoğlu & Arda, 2004); (Bayram & Yaman, 2017)). The severity level and the time of the disaster occurrence are considered the two main factors generating the scenarios in our research. The different severity levels are denoted as low, medium, and high; the time of occurrence is characterized by day and night ((Rezaei-Malek et al., 2016). Therefore, six disaster scenarios are created based on both factors. We assume that the affected people's health condition, transportation network, and infrastructure status are influenced by the disaster scenarios. By considering the importance of saving human lives, the possible infeasibility of uncertain parameters, and the risk attributed to decision-makers, a robust optimization approach is used to evaluate the worst-case conditions. This approach ensures each solution under given scenarios is close to the optimal values and results in solutions that are less sensitive to realizations of the data in a set of scenarios (Rezaei-Malek et al., 2016).

Immediately after an MCI, assessment teams are dispatched to the field for damage estimation. They gather some information about the affected sites and the transportation network to know the locations, needs, and accessibility of affected people. Concurrently, local SAR teams, supported by urban agencies like Red Crescent, and emergency management organizations, are allocated to affected sites to extricate and prioritize the trapped casualties. The performance of SAR operations is a major determinant of the inflow of casualties to medical centers. Moreover, in chaotic situations in the first hours after the disaster, there are usually a limited number of SAR teams to help the injured people. The total number of injured people who may need help at each site is a key uncertain parameter based on the disaster scenario. Therefore, the demand for SAR teams is much more than the available number of teams. Consequently, the optimal allocation of the limited resources in our time scope is a vital task in casualty management which can decrease the number of human losses significantly. The inflow of national teams from adjacent cities will increase the total number of available SAR teams in future periods. The capacity of each SAR team, i.e., the number of extricated people per period, is a known parameter.

After the extrication, rescued casualties are usually categorized into four triage groups including black, red, yellow, and green ordered by the severity of injuries. The green group is not at a high risk while the black group is not expected to survive. Therefore, relief resources majorly focus on the serious-injured groups; i.e., red and yellow. Considering the uncertainty in the number of casualties, the proportion of casualties who are to be positioned in each triage group is a scenario-dependent parameter. Red and yellow triage groups need fast stabilizing medical assistance in easy-to-access Casualty Treatment Stations (CTSs) before permanent medical care in hospitals. We consider two types of on-field medical service centers: (1) permanent hospitals/medical centers (called initial CTSs hereafter) that are not damaged by the disaster, and (2) temporary medical centers (called new CTSs hereafter) that are established after the disaster in some safe places like parks, schools, malls, public parking lots, and stadiums near the affected sites which are usually identified beforehand by relief organizations. Initial CTSs with their medical capacities; i.e., medical teams, medicine, etc. may immediately be available after the disaster while new CTSs may need some periods to be established and equipped. The number of available CTSs (initial and new) is limited.

To prevent an overwhelming condition in CTSs, serious casualties with deteriorating health conditions should efficiently be allocated to CTSs. It may directly influence the number of survivors. As a result, the inflow of casualties to CTSs is controlled by the performance of SAR teams and the distribution of casualties among CTSs. Realistically, some casualties are rescued by volunteers or relatives and transported to CTSs for treatment. This is considered as another inflow of CTSs. This happens specifically in the first hours since the local SAR teams have not arrived at affected sites yet. Due to the deterioration of the health condition, casualties are allocated to CTSs located in their radius to receive treatment timely. Travel times between affected sites and CTSs are changed based on the degree of damage to the corresponding links. Some links between affected sites and CTSs would partially be damaged or completely blocked based on the disaster scenario. The red casualties will have a priority in allocation to initial CTSs because initial CTSs are more likely to have advanced equipment than new CTSs. The number of casualties that can be transported from affected sites to both types of CTSs is limited based on the capacity of the transportation network. It is a scenario-dependent parameter that also changes over time because of the new arriving vehicles or the disruption in the connecting link between affected sites and CTSs.

The efficient management of medical teams in the first hours after a disaster considering a large and volatile amount of demand and a limited number of local urban teams is a very challenging task. Some national teams from neighboring cities are dispatched to the affected sites; therefore, the total number of available medical teams increases over time.

There are different treatment strategies, i.e., allocation of medical teams to seriously injured casualties, in CTSs influenced by the number of people in red and yellow triage groups and the number of medical teams. Red and yellow groups of casualties have different treatment times due to various injury levels. We consider two streams of medical teams and each one treats one group of casualties in CTSs. As mentioned before, the number of casualties in triage groups and the number of medical teams change over time; so, the number of medical teams allocated to each stream is allowed to overflow to another stream. The allocation of medical teams is influenced by the number of rescued people arriving at CTSs as an output of SAR operations. Therefore, the coordination of SAR and on-field treatment operations is necessary.

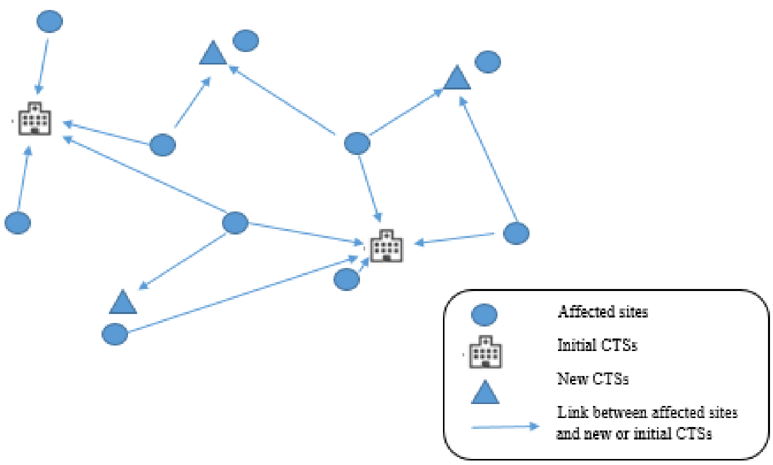


Fig. 1. The scope of the research problem

Our model is to maximize the survivors in a 12-hour planning horizon after a sudden-onset MCI. The most popular objective function in casualty management is to maximize the number of survivors. It is consistent with the approach of "considering the whole population rather than the individual" and "providing the greatest good for the greatest number of people" recommended for disasters (Rezapour et al., 2018).

In the proposed robust optimization approach, the optimal solution is feasible under the realization of each scenario and the objective function remains near its expected value. Two concepts of robustness were introduced by (Mulvey et al., 1995). Solution robustness that guarantees the optimal solution remains close to the optimum for any occurrence of the scenario, and model robustness makes the solution almost feasible for any occurrence of the scenario. A parameter is considered to penalize the model and solution robustness and capture the decisionmaker's preference ((Bozorgi-Amiri et al., 2013). The variables are categorized into design and control groups. Design variables are decided before the realization of stochastic parameters and control variables are subject to the adjustment when a specific occurrence of uncertain parameters is realized ((Pan & Nagi, 2010). In this method, the variability term is simply added to the main objective function with an associated weighting parameter representing the risk tolerance of the decision-makers ((Bozorgi-Amiri et al., 2013). This method is chosen because we want to consider uncertainties via the discrete scenarios and both the model and solution robustness simultaneously in this research.

(Soyster, 1973) proposed a robust optimization approach that considers a box set uncertainty for parameters. He used robust optimization to solve linear programming problems and found solutions that can be feasible with all data belonging to a convex set and uncertainty under all possible distributions. The resulting model produces solutions that are too conservative in the sense that we give up too much optimality for the nominal problem to ensure robustness.

(Ben-Tal & Nemirovski, 1998) proposed less conservative models by considering uncertain linear problems with ellipsoidal uncertainties, which involve solving the robust counterparts of the nominal problem in the form of conic quadratic problems. With properly chosen ellipsoids, such a formulation can be used as a reasonable approximation to more complicated uncertainty sets. However, a practical drawback of such an approach, is that it leads to nonlinear, although convex, models, which are more demanding computationally than the earlier linear models by (Soyster, 1973). (Bertsimas & Sim, 2004) proposed an approach for robust linear optimization that retains the advantages of the linear framework of (Soyster, 1973) and offered control on the degree of conservatism for every constraint. In the above approaches, the uncertain set should be continuous while this is the case in our research.

In this research, we answer the following questions in an integrated manner:

How is the allocation of local SAR teams to affected sites?

How is the allocation of extricated casualties to CTSs?

How is the allocation of medical teams to CTSs?

How is the allocation of medical teams to serious casualty groups?

The assumptions of the proposed model are summarized below.

SAR teams triage the extricated casualties before transportation to CTSs. Therefore, the triage group of casualties is known for treatment.

Both types of CTS can provide stabilizing medical services for two groups of casualties.

The number of local teams has changed over time but their movements among the affected sites and CTSs are not considered. The inflow of relief teams from national regions is taken into account. So, CTSs may work independently.

Unserved casualties in a period will be moved to the next period while the health condition of casualties deteriorates over time.

The overflow of medical teams among two triage groups is allowed with no time or cost.

Relief teams cannot interrupt their services during time intervals.

When a new CTS is established, it remains open in the next periods.

The capacity of medical teams in initial CTSs is more than that in new CTSs.

The number of medical teams in initial CTSs changes over time; but, new allocations in the next periods are not considered.

The contributions of this paper are as follows:

Considering a dynamic environment can make the model more realistic than static models. The percentage of casualties in each triage group changes over time. Also, the volunteer operations impact the number of casualties. The allocation of relief teams to affected sites and CTSs is dynamic as well.

Uncertainty as an inevitable element in post-disaster conditions is taken into account in the model based on potential scenarios. Developing scenarios with a robust model, considering both model and solution robustness, helps to take into account the risk attitude of decision-makers.

The unavailability of some facilities in the first hours after the disaster is considered due to damage to some existing CTSs and the need for some periods to establish new CTSs.

Link disruption is involved with the damage-dependent travel time in the model. The more severe damage on each link, the longer the travel time is. Also, some routes might be blocked after the disaster. To the best of our knowledge about the disaster relief management literature, (Shiripour & Mahdavi-Amiri, 2019) developed the function for travel time dependent on damage level.

Distributing the casualties considering travel time between affected sites and CTSs due to deteriorating health conditions and also the type of CTS is developed.

In order to formulate the mathematical model, the notation is as follows.

Sets and indices

$i \in I$	Affected areas
$t \in T$	Set of Periods
J'	A Set of initial CTSs is available
J''	Set of potential nodes that new CTS are established
$j \in J(J' \cup J'')$	Set of all CTSs
$s \in S$	Set of scenarios

Variables

$W_{i,t}^{u}$	Number of SAR teams allocated to node $i \in I$ at period $t \in T$
$W_{j,t}^{r}$	Number of red class medical teams allocated to node $j \in J''$ at period $t \in T$
$W_{j,t}^{y}$	Number of yellow class medical teams allocated to node $j \in J''$ at period $t \in T$
$x_{i,t}^{s}$	Number of rescued people by SAR teams in node $i \in I$ at period $t \in T$ under scenario s
$x_{i,j,t}^{r,s}$	The flow of red-group casualties from node $i \in I$ to node $j \in J$ at period $t \in T$ under scenario s
$x_{i,j,t}^{y,s}$	The flow of yellow-group casualties from node $i \in I$ to node $j \in J$ at period $t \in T$ under scenario s
$y_{j,t}^{r,s}$	Number of non-treated red-group casualties in node $j \in J$ at period $t \in T$ under scenario s
$y_{j,t}^{y,s}$	Number of non-treated yellow-group casualties in node $j \in J$ at period $t \in T$ under scenario s
$z_{j,t}^{r,s}$	Number of red-group casualties treated by red-class medical teams in node $j \in J$ at period $t \in T$ under scenario s
$z_{j,t}^{y,s}$	Number of yellow-group casualties treated by yellow-class medical teams in node $j \in J$ at period $t \in T$ under scenario s

Parameters

$O_{j,t}^{s}$	Equal 1 if an initial or new CTS is opened in node $j \in J$ at period $t \in T$ under scenario s
$TC_{i,t}^{s}$	Total number of seriously injured casualties in node $i \in$ I at period $t \in T$ under scenario s
$d_{i,j}$	travel time from node $i \in I$ to node $j \in J$ in a normal condition (period)
$d'^{s}_{i,j}$	travel time from node $i \in I$ to node $j \in J$ under scenario s(period)
$e_{i,j}^{s} \in [0,1]$	Damage degree of the link between node $i \in I$ and node $j \in J$ under scenario s
$f_{i,j}^{s}$	Equal 1 if the link between node $i \in I$ and node $j \in J$ is damaged and 0 if the link is blocked
l	A coefficient that measures the effect of a damaged link on the travel time (period)
$UB_{i,j}$	Upper bound of damage for the link between node $i \in I$ and node $j \in J$
R	Maximum acceptable time for traveling between node $i \in I$ and node $j \in J$ (period)
$k_{i,j}^{s}$	Equal 1 if the vehicle travel time from node $i \in I$ to node $j \in J$ is not greater than R under scenario s
$b_{j,t}^{r,s}$	Number of casualties, rescued by volunteers, which are transported to node $j \in J$ and labeled as red-group at period $t \in T$ under scenario s

$b^{y,s}_{j,t}$	Number of casualties, rescued by volunteers, which are transported to node $j \in J$ and labeled as yellow-group at period $t \in T$ under scenario s
$\gamma^{s}_{j,t}$	The ratio of red-group casualties to all seriously injured casualties in node $j \in J$at period $t \in T$ under scenario s
v_j	The average capacity of a given SAR team in node $j \in J$(casualties per period)
m^r_j	The average capacity of a given medical team for the red group in CTS located in the node $j \in J$ (casualties per period) ($m^r_{j'} > m^r_{j''}$)
m^y_j	The average capacity of a given medical team for the yellow group in CTS located in node $j \in J$ (casualties per period) ($m^y_{j'} > m^y_{j''}$)
$P^{r,s}_t$	Survival probability of the red group if treated at period$t \in T$ after the injury under scenario s
$P^{y,s}_t$	Survival probability of the yellow group if treated at period$t \in T$ after the injury under scenario s
P^s	Probability of scenario s
NU_t	Total number of local SAR teams available in period$t$
NM_t	Total number of local medical teams available in period$t$
λ	A coefficient that measures the effect of solution robustness
ω	A coefficient that measures the effect of model robustness
M	A sufficiently large number

Below, we develop a stochastic multi-stage mathematical model for our problem.

$$d'^{s}_{i,j} = d_{i,j}\left(1 + l * e^{s}_{i,j}\right) + M(1 - f^{s}_{i,j})$$

$$f^{s}_{i,j} = \begin{cases} 1 & if \quad e^{s}_{i,j} \le UB_{i,j} \\ 0 & link\ is\ blocked \end{cases}$$

$$k^{s}_{i,j} = \begin{cases} 1 & if \quad d'^{s}_{i,j} \le R \\ 0 & otherwise \end{cases}$$

$$Max\ Z = Z = \sum_{t\in T}\sum_{j\in J}\sum_{s\in S}\left\{P^s\left(P^{r,s}_t z^{r,s}_{j,t} + P^{y,s}_t z^{y,s}_{j,t}\right)\right\} - \lambda\sum_s P^s\,(P^{r,s}_t z^{r,s}_{j,t} + P^{y,s}_t z^{y,s}_{j,t} - \sum_s P^s\,(P^{r,s}_t z^{r,s}_{j,t} + P^{y,s}_t z^{y,s}_{j,t}))^2 - \omega\sum_s P^s\sum_t\sum_j\left(\delta^{s}_{j,t} + \delta'^{s}_{j,t}\right) \tag{1}$$

The objective function (1) maximizes respectively the expected total number of survivors in red and yellow groups under all scenarios. The second and third terms in the objective function are solution and model robustness, respectively. The model is subject to the following equations:

$$x^{s}_{i,t} \le TC^{s}_{i,t}(\forall i \in I, \forall t \in T, \forall s \in S) \tag{2}$$

Constraints (2), ensure that the number of saved casualties from affected sites should not be more than the total number of casualties.

$$x^{s}_{i,t} = v_i.W^{u}_{i,t}(\forall i \in I, \forall t \in T, \forall s \in S) \tag{3}$$

Based on constraints (3) the outflow from each affected site does not violate the capacity of assigned SAR teams.

$$W^{u}_{i,t} \le NU_t\left(\frac{TC^{s}_{i,t}}{\sum_{i\in I} TC^{s}_{i,t}}\right)(\forall i \in I, \forall t \in T, \forall s \in S) \tag{4}$$

Constraints (4) allocate the SAR teams proportional to the affected sites' population.

$$\sum_j x^{r,s}_{i,j,t} = \gamma^s_{i,t}(x^s_{i,t}) \quad (\forall i \in I, \forall t \in T, \forall s \in S) \tag{5}$$
$$\sum_j x^{y,s}_{i,j,t} = (1 - \gamma^s_{i,t})(x_{i,t}) \quad (\forall i \in I, \forall t \in T, \forall s \in S) \tag{6}$$

Constraints (5) and (6) determine the percentage of saved casualties in red and yellow triage groups $\left(0 \le \gamma^s_{i,t} \le 1\right)$.

$$x^{r,s}_{i,j,t-d'^s_{i,j}} + y^{r,s}_{j,t-1} + x^{y,s}_{i,j,t-d'^s_{i,j}} + y^{y,s}_{j,t-1} \le M f^s_{i,j} O^s_{j,t} k^s_{i,j} (\forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S) \tag{7}$$

Constraint (7) allows casualties to be transported from affected sites to CTSs if the link between them is usable, the CTS is open and the affected site is in the radius of the CTS.

$$\left(\sum_i x^{r,s}_{i,j,t-d'^s_{i,j}}\right) + b^{r,s}_{j,t} O^s_{j,t} + y^{r,s}_{j,t-1} = z^{r,s}_{j,t} + y^{r,s}_{j,t} \ (\forall j \in J, \forall t \in T, \forall s \in S) \tag{8}$$
$$\left(\sum_i x^{y,s}_{i,j,t-d'^s_{i,j}}\right) + b^{y,s}_{j,t} O^s_{j,t} + y^{y,s}_{j,t-1} = z^{y,s}_{j,t} + y^{y,s}_{j,t} \ (\forall j \in J, \forall t \in T, \forall s \in S) \tag{9}$$

Constraints (8) and (9) ensure the inflow and outflow balances on red and yellow groups of casualties, respectively, in CTSs. In each CTS, the sum of untreated casualties from the previous period and the arrived saved casualties should be equal to the sum of treated casualties in the current period and the untreated casualties left for the next time unit.

$$z^{r,s}_{j,t} \le m^r_j W^r_{j,t} (\forall j \in J, \forall t \in T, \forall s \in S) \tag{10}$$
$$z^{y,s}_{j,t} \le m^y_j W^y_{j,t} (\forall j \in J, \forall t \in T, \forall s \in S) \tag{11}$$

The capacity of assigned teams to a CTS in each stream should not be violated by the number of treated casualties in constraints (10) and (11).

$$\sum_t \sum_j (z^{y,s}_{j,t}) \le \sum_t \sum_j (1 - \gamma^s_{i,t})(z^{r,s}_{j,t} + z^{y,s}_{j,t}) + \delta'^s_{j,t} \ (\forall s \in S) \tag{12}$$

Constraints (12) make the number of survivors in the yellow group should not be more than $\left(1 - \gamma^s_{i,t}\right)$ of total survivors. This term can be interpreted as fairness. Because the objective function intends to maximize the yellow group of casualties who have a higher survival probability. This limitation makes the number of survivors in each group proportional to the percentage of the total serious-injured casualties.

$$\sum_j (W^r_{j,t} + W^y_{j,t}) = NM_t (\forall t \in T) \tag{13}$$
$$x^s_{i,t}, x^{r,s}_{i,j,t}, x^{y,s}_{i,j,t}, y^{r,s}_{j,t}, y^{y,s}_{j,t}, z^{r,s}_{j,t}, z^{y,s}_{j,t}, W^u_{j,t}, W^r_{j,t}, W^y_{j,t} \ge 0 \quad (\forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S) \tag{14}$$

Constraints (13) impose that the number of assigned medical teams is limited to the available number of teams in each period in both initial CTSs and new CTSs. Constraints (14) are for non-negative variables.

Numerical Analysis

Experimental setting

In this subsection, the experimental setting is presented, and then analyzing and comparing the proposed model are committed. The period is assumed to be 30 minutes. Table 1 shows the survival probabilities for the red and yellow triage groups (Dean & Nair, 2014). In this section, the investigation of model performance is considered through different experimental analyses. We consider three levels of severity, namely low, medium, and high, and two times of disaster, day and night. Therefore, six scenarios are generated based on all combinations of these factors and the parameters are different in them. Uncertain parameters are generated randomly in specific intervals. The planning horizon is considered fixed and the problem size is determined based on the number of nodes, as an important determinant. It generated 80 instances for each scenario in four problem sizes (5, 10, 15, 20, and 30 nodes). The scenario and parameters depending on the scenario are summarized in Table 1. Table 2 shows the parameters independent of the scenario. The number of opened CTSs and the number of SAR teams and medical teams has increased over time. The number of damaged links increases in terms of scenarios.

Table 1. All possible scenarios and scenario-dependent parameters.

	Scenario 1	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**	**Scenario 6**
Scenario (severity, time)	**Low, day**	**Low, night**	**Medium, day**	**Medium, night**	**High, day**	**High, night**
Probability	0.5*0.5=0.25	0.5*0.5=0.25	0.3*0.5=0.15	0.3*0.5=0.15	0.2*0.5=0.1	0.2*0.5=0.1
$\gamma_{j,t}^{s}$	[0,0.2]	[0.1,0.3]	[0.2,0.4]	[0.3,0.5]	[0.4,0.6]	[0.5,0.7]
$TC_{i,t}^{s}$	[1٠0,2٠0]	[150,300]	[200,400]	[300,500]	[400,700]	[500,1000]
$b_{j,t}^{y,s}, b_{j,t}^{r,s}$	[20,70]	[50,100]	[70,130]	[100,150]	[120,170]	[150,200]

Table 2. Details of Generating random values for parameters.

Input Parameters	**Value, Range**
N	{5,10,15,20}
J	{1,3,4,6,8}
$O_{j,t}$	Random generation
l	[5,10] (Minutes)
R	[15,25] (Minutes)
$UB_{i,j}$	{0.55,0.7}
v_j	{12,15,20}
m_j^r	{7.5,9.1,11.5}
m_j^y	{10,12,15}
NU_t	{1,…,200}
NM_t	{1,…,200}
λ	{1,10,100}
ω	{1,10,100}

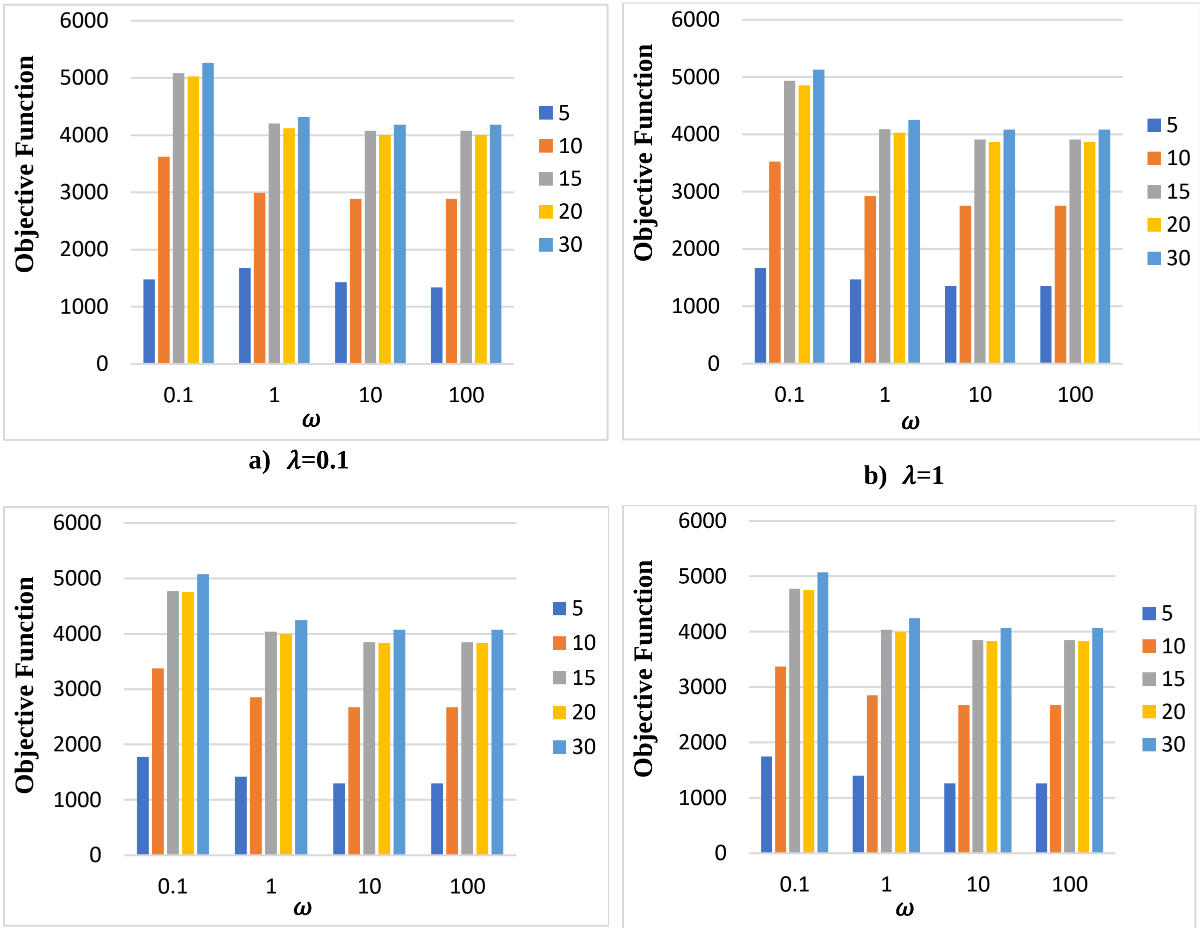
Sensitivity Analysis

In this subsection, the sensitivity of the model is analyzed against solution and model robustness. As can be seen in Table 3, the values of the objective function for the robust model are less than the stochastic model. Because the robust model considers the worst case and the solution of each scenario tends to be close to its average. It is useful for the risk-averse decision-makers who consider a worst-case scenario.

Table3. The objective function for stochastic and robust model. $\lambda = \omega = 10$

Problem size	**Stochastic**	**Robust**
5	1311.576	1280.122
10	2551.302	2372.238
15	4103.426	3899.39
20	4108.97	3997.533
30	4385.25	4070.434

Our robust counterpart problem studies both solution robustness and the model robustness concepts simultaneously. The performance of the model based on different values of solution robustness and model robustness (λ and ω) is shown in Fig. 2. (a, b, c, and d) for different sizes of networks. The objective function for the low values of ω, is higher than it is for high values of this parameter. This is true for all network sizes.



a) λ=0.1 b) λ=1 C) λ=10 d) λ=100

Fig. 2. The objective function for 5 sizes of network.

Considering the importance of saving human lives, the robust optimization approach is used to consider the worst-case conditions. The solution robustness guarantees each solution remains close to optimal and the model robustness ensures the solution remains feasible for any realization of the scenario. This approach results in solutions that are less sensitive to realizations of the data in a set of scenarios. Therefore, the high values for λ and ω make the model risk-averse, and low values lead to risk-taking.

Conclusions

There are a large number of injured people in a short time and also, various uncertainties in the chaotic circumstance after a sudden onset incident. Therefore, in this research, we have developed a robust stochastic model corresponding to on-field relief operations in the first hours after a disaster. The uncertainty is taken into account through some plausible scenarios. The proposed model simultaneously allocated SAR teams to the affected sites, medical teams and extricated casualties to the CTSs, and medical teams to the casualty groups intending to improve the expected number of survivors considering link disruption, unavailability of CTSs, deterioration over time in survival probability. The objective function maximizes the expected number of survivors. Considering the importance of saving human lives, the possible infeasibility of uncertain parameters, and the risk attributed to decision-makers, the robust optimization approach is used to consider the worst-case conditions. This approach ensures each solution under given scenarios is close to the optimal values and results in solutions that are less sensitive to realizations of the data in a set of scenarios. The numerical study was established by generating 80 random instances to evaluate the performance of the proposed optimization model. The robust model that tries to maintain the optimal solution under given scenarios close to its expected value results in fewer survivors. Applying another robust approach, considering the transportation of casualties to hospitals and the selection of hospitals, can be important directions for future research. Also, the models with behavioral aspects are another avenue for study, because both families that have lost their members and all responders (relief teams, doctors, transporters, etc.) are in severe mental health difficulties after the disaster.

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