Advances in Industrial Engineering, Winter 2022, 56(1): 43-55
DOI: 10.22059/AIE.2022.337140.1820
RESEARCH PAPER

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

Atefe Baghaian, Mohammad Mehdi Lotfi *

Department of Industrial Engineering, Faculty of Engineering, Yazd University, Yazd, Iran.

Received: 10 January 2022 Revised: 26 February 2022, Accepted: 01 March 2022

Abstract

Assigning a limited number of relief teams to casualties immediately after a disaster is a challenging task in the casualty management process. This paper proposes several dynamic strategies for allocating teams to casualty groups right after a sudden-onset disaster to maximize the expected number of survivors. In the proposed strategies, serious triage groups and the deterioration of the physical condition of injured people are considered. The ratio of casualties in two critical triage groups, and the treatment rates and survival probabilities are the main parameters of the strategies. Thereafter, a case study is employed to demonstrate the validity of the proposed model. The strategies are compared based on the summation of the ratio of casualties in two triage groups. This comparison represents that the saving rate may be considered as an appropriate ratio for assigning medical teams to casualty groups. Sensitivity analysis evaluates the impact of key parameters on the model results. Accordingly, changes in the ratio of triaged people have less effect on the ratio of survivors than changes in the treatment rates. It indicates the importance of relief teams' allocation for surviving the casualties.

Keywords:
Casualty Management;
Search and Rescue;
Triage;
On-Field Treatment;
Dynamic Team Allocation

Introduction

Natural disasters such as earthquakes, floods, and hurricanes make a significant loss in human lives, infrastructures, and community properties. Therefore, efficient management of disasters is an important issue that policymakers in disaster-prone countries have been confronted with in recent decades. Among four phases of the disaster management; i.e., mitigation, preparedness, response, and recovery, the third one is the most challenging due to the limitations of relief resources (e.g., rescue and medical teams, transportation fleet, and relief items), the time pressure due to increasing the death probability of casualties over time, and the lack of sufficient data (i.e., the number and location of affected sites and casualties). These challenges are of more criticality in the initial hours after disasters in which the survival probability of casualties is higher but relief resources accessible in affected sites are very limited.

In the stressful environment after disasters, a lot of people may be injured and in need of first-aid assistance to stabilize their medical conditions before being taken to hospitals. This function that is called "stabilization operation" is considered as one of the most important operations in the response phase to maximize the number of survivors (Rezapour et al. [17]). Farahani et al. [5] categorize life-saving operations in the response phase into five groups: (1)

* Corresponding author: (M.M. Lotfi)
Email: Lotfi@yazd.ac.ir

Rescue Operation – this operation includes dispatching rescue teams to affected sites to search, locate, and extract trapped casualties (e.g., in collapsed buildings and bridges), (2) ***Triage Operation*** – in this operation, casualties are categorized according to their injury levels and prioritized for medical treatment under the lack of efficient medical resources/teams. Several triage methods were proposed in the literature such as Simple Triage and Rapid Treatment (START) (Super et al. [23], Triage Sieve (Hodgetts and Macway-Jones [8]), Sacco Triage Method (Sacco et al. [20]), Sort, Assess, Life-saving interventions, Treatment and/or Transport (Lerner et al. [11]), and Severity Adjusted Victim Evacuation (Dean and Nair [4]). START, as the most common triage method, categorizes casualties into four groups labelled by red, yellow, green, and black colours, (3) ***Stabilization Operation*** – after extrication and triage, casualties, for the first aid assistance, are transported to temporary medical centres established on the field, (4) ***Transportation Operation*** – casualties who need further medical interventions (e.g., surgery and hospitalization) are transported from on-field medical centres to nearby hospitals, and (5) ***Hospitalization Operation*** – Transported casualties to each hospital are prioritized for hospitalization and receive complete treatment under the lack of sufficient beds.

The focus of this paper is on the stabilization operation which depends on the allocation of medical resources/teams to different casualty groups having different injury levels and survival probabilities. In this paper, we focus on a given medical centre in an affected site and develop several strategies (DASs) for assigning rescue and medical teams to casualties in a dynamic manner while the number of teams is known. The casualties are extracted by the rescue resources/teams in the affected site and sent to the medical centre for medical stabilization. The proposed DASs assign medical resources/teams to casualty groups in a way to maximize the expected number of survivors. The green casualty group is not in danger of death and the black group is not expected to survive even after a medical intervention. Therefore, we focus on the red and yellow casualty groups as two critical groups that may be saved by relief teams after a disaster. Due to the lack of enough medical resources/teams, efficient allocation of resources/teams to red and yellow casualty groups can significantly increase the number of survivors.

The rest of the paper is organized as follows. Section 2 contains a review of the relevant literature. Section 3 provides a detailed problem definition and mathematical formulation for the problem. Numerical results are discussed in Section 4. Finally, Section 5 concludes the paper and proposes some future research directions.

Literature review

In recent decades, many scholars have studied subjects in the field of casualty management. Farahani et al. [5] reviewed the relevant papers and categorized them according to their features such as objective functions, decisions, assumptions, and limitations. They used this classification to identify research gaps and determine future research directions that need more investigation. Since this study addresses the on-field treatment in temporary medical centres, we only review the papers that considered locating medical centres and planning their activities.

Locating On-field Medical Centres

Sabouhi et al. [19] developed a location-routing model to transport the evacuees from affected areas to shelters. The location of shelters, and routing and scheduling of relief vehicles should be determined. The objective function minimized the total transportation time. Zafari and Shishebori [25] introduced a problem to minimize arrival times. Alizade et al. [2] proposed a model for locating casualty collection points, allocating affected sites to the points, and assigning these points and their casualties to hospitals. Liu et al. [13] developed a model to locate on-field medical centres. This model allocated rescue resources (e.g., helicopters and ambulances) to centres in a way to maximize the expected number of survivors and minimize the total operational cost.

Li et al. [12] developed a scenario-based three-stage model to locate medical facilities and plan casualty transportation in a way to minimize the total costs (sum of fixed cost of locating facilities, transportation cost of casualties, and penalty cost for un-evacuated victims). A customized progressive hedging algorithm was developed to solve the problem. Oksuz and Satuglu [16] developed a two-stage stochastic model to determine the location of medical centres and allocation of casualties to them in a way to minimize the total setup and transportation cost. Sun et al. [21] determined the location of emergency medical services and transportation of casualties to these centres. Robust optimization was employed to cope with uncertainties in parameters. Sun et al. [22] studied the facility location, casualty transportation, and allocation of rescue vehicles. Robust optimization and e-constraint approaches were used to solve the model. In all of these papers, the treatment operations within medical centres were ignored. This research gap is bridged in this paper.

Treating Casualties in Medical Centres

Lodree et al. [14] proposed a model to optimize the allocation of doctors, nurses, and their combinations (called servers) to casualty queues in a medical centre. They used stochastic dynamic programming to minimize the expected holding costs in the centre. But, the deterioration of the physical condition of casualties over time was not considered. We formulate the time-decreasing survival probabilities for casualty groups to consider it. Rezapour et al. [18] studied the allocation of relief teams to affected sites and casualty groups. They assumed that casualties arrive at the medical centre according to the Poisson process with a fixed rate. They assumed that the number of relief teams is fixed over time. Rezapour et al. [17] developed a model to optimize the treatment strategy considering the spatial dispersion of casualties and temporal variations of emergency resources. Maximizing the survivors' number was as the objective function. The treatment rate in a single treatment station was fixed. To maximize the expected number of survivors, Baghaian et al. [3] developed some treatment strategies in medical centres; but, they assumed fixed parameters over time. Unfortunately, the deterioration of physical conditions of yellow casualties was not considered in recent papers causing their movement to the red group.

Transporting Casualties to Hospitals

Most of the current papers in the literature focus on the transportation of casualties from affected sites to hospitals. For example, Mills et al. [15] developed a model to prioritize the transportation of casualties from an affected site to hospitals. They employed three-parameter survival probability functions for different triage groups that deteriorate over time. Dean and Nair [4] proposed SAVE (Severity- Adjusted Victim Evacuation) model to prioritize the process of transporting casualties to hospitals in a way to maximize the expected number of survivors. Using a fuzzy chance constraint programing, Alinaghian et al. [1] developed a relief vehicle routing model to minimize the total response time. Jin et al. [9] studied the casualty transportation in a three-layer relief network under the transportation fleet limitation. Similarly, Kamali et al. [10] developed a model to determine the order of transporting casualties by the limited number of ambulances to hospitals. Zhu et al. [26] proposed a multi-objective mathematical model for routing of vehicles among affected sites and temporary medical stations. The objective functions of the model are minimizing the transportation costs and deprivation costs. Feng et al. [6] considered the problem of hospital transportation taking into account the injury classification and survival probability. Ant colony optimization algorithm was used to solve the problem.

To highlight the novelties of our model and its contribution to the literature, the most related papers are summarized in Table 1 and their important features are detailed.

Table 1. Literature review

References	Search and rescue	Triage operation	On-field treatment	Decisions	Dynamic parameters	Objective function	Solution approach
Alizade et al. [2]	-	✓	✓	-Locate medical centres -Allocate casualties to medical centres	Casualty flow	Minimize total costs	Linear Programming
Lodree et al. [14]	-	-	✓	Allocate teams to casualty queues	-Arrival rate of casualties -Treatment rate	Minimize total costs	Dynamic programming
Liu et al. [13]	-	-	✓	Allocate casualties to medical centres	Survival probability	Maximize expected number of survivors and minimize total operational cost	Linear Programming
Rezapour et al. [18]	✓	✓	✓	Allocate teams to casualty groups	Survival probability	Maximize expected number of survivors	Queue theory
Sun et al. [21]	✓	✓	-	Allocate casualties to medical centres	Survival probability	Injury Severity Score	Linear Programming
Sun et al. [22]	✓	✓	-	Allocate casualties to medical centres	Survival probability	Minimize injury severity score and Minimize total costs	Linear Programming
Rezapour et al. [17]	✓	✓	✓	Allocate teams to casualty groups	Survival probability	Maximize expected number of survivors	Simulation
Baghaian et al. [3]	✓	✓	✓	Allocate teams to casualty groups	Survival probability	Maximize expected number of survivors	Linear Programming
This study	✓	✓	✓	Allocate teams to casualty groups	-Survival probability -Arrival rate -Treatment rate -Deterioration of yellow group	Maximize expected number of survivors	Linear Programming

The main contributions of this study are as follows:

(1) Due to the variation in the number of relief resources, we assume that the arrival rate of casualties at the medical centre is dynamic. Most of the previous papers assumed that all casualties are available at time zero and they ignored the search and rescue operation in the casualty management (Mills et al. [15]; Dean and Nair [4]; Kamali et al. [10]). In our study, we assume dynamism in the number of teams, the rescue rate and the treatment rate. The number of casualties in the red group changes over time.

(2) The physical condition of casualty groups is considered to be dynamic and deteriorates over time. Yellow casualties are turned to red if they are not treated on time.
(3) Several novel DASs are developed to allocate medical teams to casualty groups in a dynamic environment.

Problem definition

Providing medical services for a huge number of casualties in the first hours after a mass-casualty incident (MCI) is a challenging issue. In this paper, we consider an urban area which has severely been stricken by a sudden-onset disaster such as an earthquake. Due to the high population density, there might also be a huge number of seriously injured casualties trapped in collapsed buildings, damaged bridges, crashed cars, etc. These casualties should be extricated (by search and rescue teams) and medically stabilized (by on-site medical teams), before transportation to hospitals for a comprehensive treatment. Therefore, urban search-and-rescue (USAR) and medical teams are usually dispatched to the affected sites in order to provide relief operations in some on-site temporarily-established facilities called casualty treatment stations (CTSs). Due to a large number of casualties and limited number of medical teams, the allocation of teams to the casualty groups has an important role in the efficiency of casualty management operation.

In the affected sites, rescued casualties by USAR teams are categorized into four triage groups according to their injury levels (Mills et al. [15]), and then sent to CTS to receive first aid assistance. We only consider red and yellow casualties whose physical conditions deteriorate over time if they do not receive medical interventions. CTS is located on safe points near the affected sites. It is assumed that the survival probability of each triage group is a decreasing function of time. If yellow-group casualties do not receive medical services on time, their triage group might be turned to red. So, the triage is repeated in specific time intervals for waiting casualties who still have not received any services. In each triage repetition, the triage group of some waiting casualties may change. The main question of our research is how to allocate the medical teams to casualty groups considering the search and rescue in which the expected number of survivors is maximized.

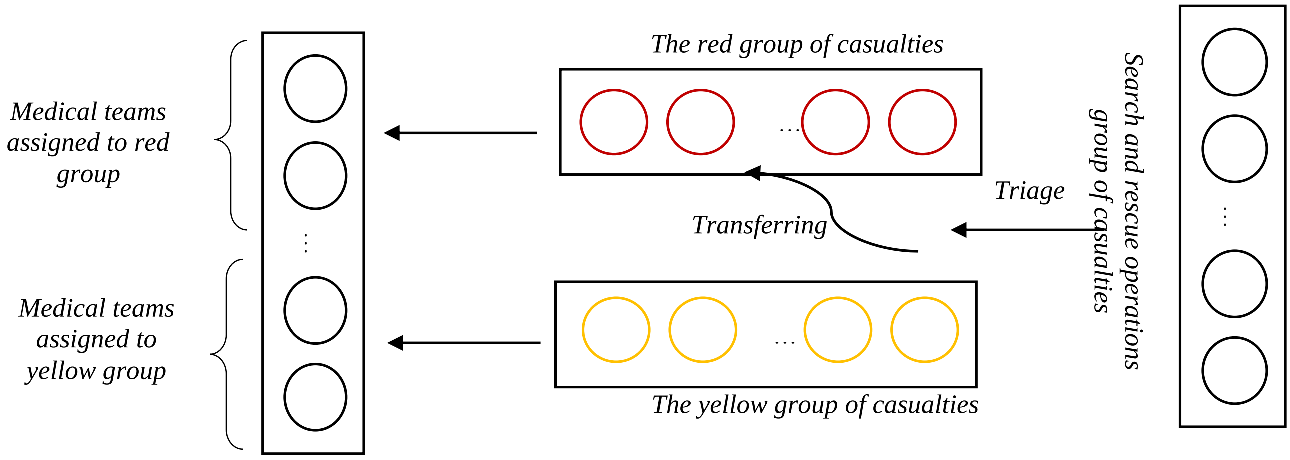

Fig. 1. Our problem

The number of USAR and medical teams in each time unit are known and may change over the planning horizon because new teams may be dispatched to the affected sites and CTSs. The rescue rate of each USAR team in each time unit (i.e., the number of casualties rescued by a USAR team in each time unit) may change over time because the density of casualties in the affected sites is usually high in the first hours after the disaster and starts to decrease after that. The treatment rate of a medical team in each time unit may also change over time. The severity of the disaster may be different in the affected sites and the ratio of red casualties is not the same. Therefore, the ratio of red casualties to total casualties is changed over time period. In each time unit, some yellow casualties who do not receive a service, are transferred to the red group. A general structure of the investigated problem is represented in Fig. 1.

In this paper, we analyse the performance of DASs. They assign medical teams to casualty groups in six different ways: in the first three strategies, the number of teams allocated to the red group is less than that to the yellow group whereas the last three strategies are the inverse of the first three ones:

1. Strategy 1: The medical teams are allocated to casualty groups proportional to number of casualties in those groups:
$$\frac{Number\ of\ teams\ allocated\ to\ the\ red\ group}{Number\ of\ teams\ allocated\ to\ the\ yellow\ group}=\frac{Ratio\ of\ red\ casulaties}{Ratio\ of\ yellow\ casualties}$$
2. Strategy 2: The medical teams allocated to casualty groups proportional to treatment rate of casualties in those groups:
$$\frac{Number\ of\ teams\ allocated\ to\ the\ red\ group}{Number\ of\ teams\ allocated\ to\ the\ yellow\ group}=\frac{Treatment\ rate\ of\ red\ casulaties}{Treatment\ rate\ of\ yellow\ casulaties}$$
3. Strategy 3: The medical teams allocated to casualty groups proportional to survival probability of casualties in those groups multiplied by their treatment rate (This shows saving rate of casualties by a medical team):
$$\frac{Number\ of\ teams\ allocated\ to\ the\ red\ group}{Number\ of\ teams\ allocated\ to\ the\ yellow\ group}=\frac{Survival\ probability\ of\ red\ casulaties\times Treatment\ rate\ of\ red\ casulaties}{Survival\ probability\ of\ yellow\ casulaties\times Treatment\ rate\ of\ yellow\ casulaties}$$
4. Strategy 4: Allocating medical teams to casualty groups as follows:
$$\frac{Number\ of\ teams\ allocated\ to\ the\ red\ group}{Number\ of\ teams\ allocated\ to\ the\ yellow\ group}=\frac{Ratio\ of\ yellow\ casulaties}{Ratio\ of\ red\ casualties}$$
5. Strategy 5: Allocating medical teams to casualty groups as follows:
$$\frac{Number\ of\ teams\ allocated\ to\ the\ red\ group}{Number\ of\ teams\ allocated\ to\ the\ yellow\ group}=\frac{Treatment\ rate\ of\ yellow\ casulaties}{Treatment\ rate\ of\ red\ casulaties}$$
6. Strategy 6: The medical teams are allocated to casualty groups as follows:
$$\frac{Number\ of\ teams\ allocated\ to\ the\ red\ group}{Number\ of\ teams\ allocated\ to\ the\ yellow\ group}=\frac{Survival\ probability\ of\ yellow\ casulaties\times Treatment\ rate\ of\ yellow\ casulaties}{Survival\ probability\ of\ red\ casulaties\times Treatment\ rate\ of\ red\ casulaties}$$

We aim to allocate local medical teams to serious casualty groups in a CTS in a way to maximize the expected number of survivors. The formulation of basic model is as follows:

Set and index

T	Set of time units within the planning horizon indexed by t
K	Set of casualty groups indexed by k ($k=r$ for red group and $k=y$ for yellow group)

Parameters

TC	The total number of casualties
e_k^t	Treatment time of casualties of type k at time unit t
γ_k^t	The ratio of casualties belongs to type k at time unit t ($\gamma_r^t+\gamma_y^t=1$)
v^t	The rescue rate of each USAR team at time unit t
m_k^t	The treatment rate of each medical team for casualties from type k at time unit t
p_k^t	The survival probability of casualties of type k if treated at time unit t
NU^t	The total number of USAR teams available in the affected site at time unit t
NM^t	The total number of medical teams available in the CTS at time unit t

Variables

λ_k^t	The number of medical teams assigned to casualties of type k at time unit $t \in T$ ($\lambda_r^t + \lambda_y^t = 1$)
X^t	The number of casualties rescued at time unit t
Y_k^t	The number of transferred casualties of type k to the CTS at time unit t
W'^t	The number of yellow casualty group transferred to red triage group at time period t
W_k^t	The number of untreated casualties of type k at time unit t
S_k^t	The number of casualties of type k whose treatment starts at time unit t
Z_k^t	The number of treated casualties of type k at time unit t

$$\textbf{\textit{Max}}\ Z = \sum_t \sum_k p_k^t . Z_k^t \tag{1}$$

S.T.

$$X^t \leq TC \tag{2}$$

$$X^t \leq v^t . NU^t (\ \forall t \in T) \tag{3}$$

$$Y_k^t = \gamma_k^t . X^t\ (\forall t \in T) \tag{4}$$

$$W_r^t = Y_r^t + W_r^{t-1} + W'^{t-1} - S_r^t \tag{5}$$

$$W_y^t = Y_y^t + W_y^{t-1} - W'^{t-1} - S_y^t \quad (\forall t \in T) \tag{6}$$

$$Z_k^t = Z_k^{t-1} + S_k^t - S_k^{t-e_k^t} \tag{7}$$

$$Z_k^t \leq m_k^t . \lambda_k^t . NM^t (\forall t \in T) \tag{8}$$

$$X^t, Y_k^t, Z_k^t, S_k^t, W_k^t, \lambda_k^t \geq 0 \quad (\forall t \in T) \tag{9}$$

The objective function (1) maximizes the expected number of survivors. Constraint (2) ensures that the number of rescued casualties in the affected site cannot be more than the total number of casualties. Based on Constraint (3), the number of rescued casualties cannot be higher than the capacity of USAR teams. Constraint (4) determines the number of rescued casualties belonging to each triage group. The number of red casualties in each time unit (constraint (5)) is equal to the number of yellow casualties moved to the red group, plus the number of red casualties waiting from the previous period, plus the number of red casualties arriving at the CTS, and minus the number of red casualties already treated by the medical teams. Constraint (6) is the same as Constraint (5) but for yellow casualties. Constraint (7) states that the number of treated casualties in each time unit is equal to the sum of the number of treated casualties in the previous time unit and the number of casualties who started their treatment minus the number of casualties who ended their treatment. According to constraint (8), the number of treated casualties in each group cannot be more than the treatment rate of allocated teams. Constraint (9) denotes the nonnegative variables.

A constraint is included in the model to formulate each DAS.

Strategy 1: $$\lambda_r^t = \left(\frac{\gamma_r^t}{\gamma_y^t}\right) . \lambda_y^t \tag{10}$$

Strategy 2: $$\lambda_r^t = \left(\frac{m_r^t}{m_y^t}\right) . \lambda_y^t \tag{11}$$

Strategy 3: $$\lambda_r^t = \left(\frac{p_r^t . m_r^t}{p_y^t . m_y^t}\right) . \lambda_y^t \tag{12}$$

Strategy 4: $$\lambda_r^t = \left(\frac{\gamma_y^t}{\gamma_r^t}\right) . \lambda_y^t \tag{13}$$

Strategy 5: $$\lambda_r^t = \left(\frac{m_y^t}{m_r^t}\right) . \lambda_y^t \tag{14}$$

Strategy 6: $$\lambda_r^t = \left(\frac{p_y^t . m_y^t}{p_r^t . m_r^t}\right) . \lambda_y^t \tag{15}$$

Case study

In this section, the model performance is investigated through a case study from Kermanshah earthquake, 2017. The model is implemented using CPLEX solver of GAMS software. In Subsection 4.1, the values of main parameter are presented and the computational analysis is explained in Subsection 4.2. The sensitivity analysis and managerial insights are provided in Subsections 4.3 and 4.4, respectively.

Data collection

Kermanshah located in northeast of Iran experienced an extremely high 7.3 magnitude earthquake in November 2017. During this incident, 630 people died, more than 8,100 were injured, about 70,000 became homeless, and the main hospital of this province was destroyed (Haeri et al. [7]). Due to the significant level of threats in this area, existing four major faults (High Zagros Fault, Mountain Front Fault, Sahneh Fault and Morvarid Fault) are used as the case study in this work. The period of 12h after the disaster is considered and the length of each time unit is 15 minutes. The survival probabilities for red and yellow groups are calculated based on a three-parameter function adopted from Mills et al. [15].

$$pr^{k,t} = \frac{\beta_{0,k}}{\left(\frac{t}{\beta_{1,k}}\right)^{\beta_{2,k}}+1} \tag{16}$$

Because it is very difficult to estimate the parameters in the model accurately, the other parameters are adopted from the other papers (like Haeri et al. [7] and Liu et al. [13]) shown in Table 2.

Table 2. The reference of key parameters.

Parameter	Reference
TC	Estimated based on Haeri et al. [7]
γ_r^t	A number from interval (0,0.2] and $\gamma_y^t = 1 - \gamma_r^t$
m_k^t, v^t	From the literature (Rezapour et al. [18] and Jin et al. [9])
e_k^t	From the literature (Rezapour et al. [18] and Jin et al. [9])
NU^t, NM^t	Based on some related studies in the literature (Tirkolaee et al. [24] and Liu et al. [13])

Computational analysis

In this subsection, the results of the model for the proposed strategies are represented. The more the yellow treated casualties, the higher the objective function value. Because we want to consider both triage groups, another criterion is introduced. The criterion is the summation of the ratio of survivors to the triaged people in both groups (RST).

Table 3. The results for different strategies.

Strategy	Objective	Red group	Yellow group	RST
1	1033.1	86.80	2025.0	1.296014
2	732.30	186.5	1333.2	1.546730
3	911.10	172.4	1716.2	1.628334
4	158.00	186.5	171.30	1.070263
5	610.00	186.5	1094.5	1.448842
6	393.14	186.5	637.60	1.261526

According to the comparison between the strategies, the third one has the best performance. This strategy has more RST compared to the other strategies.

Sensitivity Analysis

In this subsection, the performance of the treatment strategies is analysed based on some key parameters. We consider ± 20, ± 10 errors in the values of three significant parameters: the ratio of triaged individuals and the treatment rate, and the rescue rate.

The changes in γ_k^t is analysed in Fig. 2. When the ratio of triaged casualties is increased, the value of RST for strategies 1 and 3 is decreased. This is because the number of red and yellow survivors are, respectively, in a positive and negative relationship with the ratio of red and yellow triaged victims. In contrast, the value of RST for strategies 2, 4, 5, and 6 increases when the ratio of triaged individuals is increased. As the decrease in yellow survivors is greater than the increase in red survivors, the value of RST decreases. The errors in γ_k^t have the greatest impact on strategies 2, 3, and 4.

As can be seen in Fig. 3, increasing in m_k^t makes an enhancement in the number of survivors in both groups. Then, RST increases with the increase of these parameters. As the treatment rate increases, the number of casualties treated by each medical team also increases. The effects of changes in this parameter are obviously large for strategies 1 and 3. Strategy 4 is slightly affected by these changes.

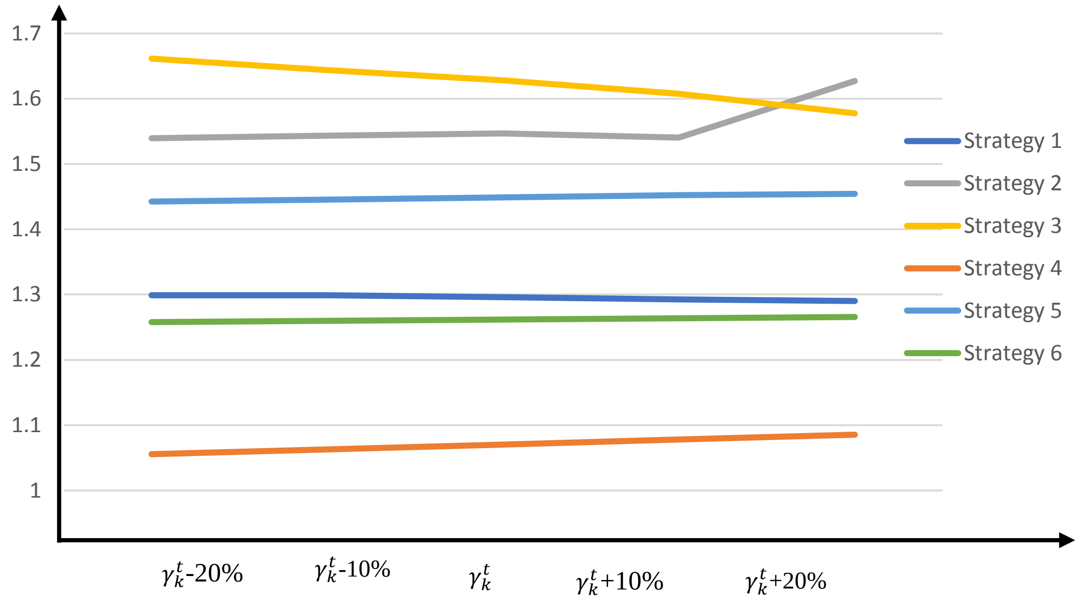

Fig. 2. The performance of strategies against variability of γ_k^t.

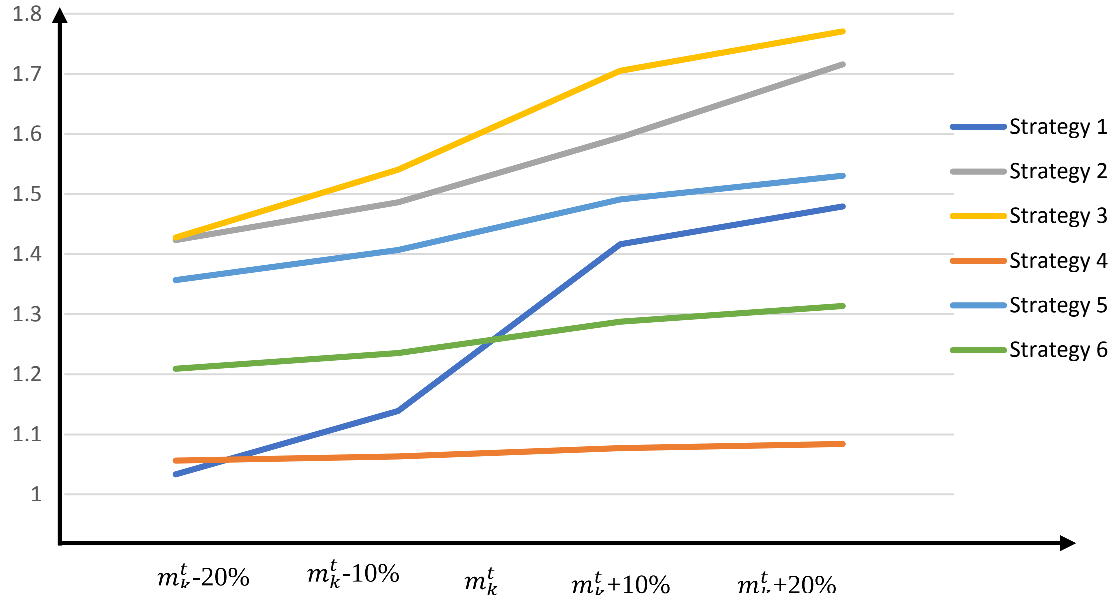

Fig. 3. The performance of strategies against variability of m_k^t.

Fig. 4 represents the errors in the rescue rate. Variation in this parameter variates the number of triaged cases. Thus, fluctuations are occurred in both the number of triaged casualties and the number of survivors with the increase in rescue rate See strategies 1, 2, and 3 *that behave the same versus* v^t. Strategies 4 and 5 are more or less stable versus v^t. But, strategy 6 differs from the others: The value of RST decreases with the increase in the rescue rate since the number of triaged people is fixed (the number of medical teams is fixed).

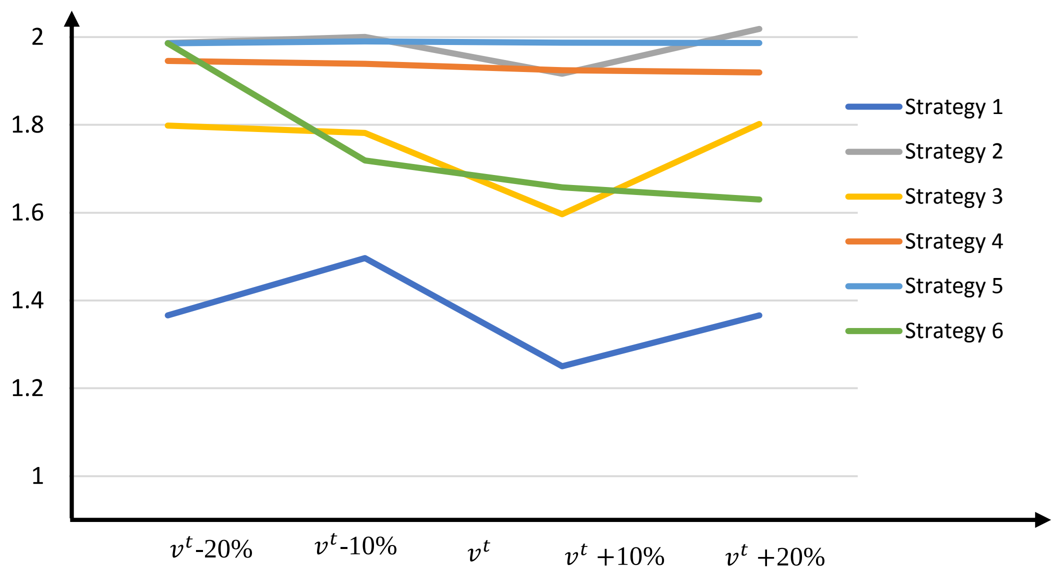

Fig. 4. The performance of strategies against variability of v^t.

Managerial insights

Considering only one triage group in time units is not fair. Although the treatment of red casualties takes a longer time than yellow casualties, neglecting a red casualty turns black which is more likely than yellow ones. On the other hand, treatment of red casualties makes the waiting time for the yellow group increase and they may turn red. Hence, the treatment rate, survival probability, and injured people in each group are the most important parameters affecting the assignment of resources to casualty groups. So, the allocation strategy is a key determinant of the number of survivors. The allocation strategy is a function of parameters shifting over time. Based on the numerical finding, the allocation of medical teams based on the third strategy overcomes other strategies. Changes in some parameters impact the performance of the strategies. This analysis makes some insights that is beneficial for decision-makers, summarized as follows:

- Saving rate is an important measure for assigning medical teams to triage groups
- Errors in the treatment rate affect the number of survivors in both groups.
- Errors in γ_k^t affect RST less than errors in m_k^t.

Conclusion

After a disaster, there are a large number of injured people in a short time and providing on-time emergency medical aids is essential. In this paper, a mathematical model was developed for the allocation of relief teams to maximize the expected number of survivors considering the physical condition of casualties. Some strategies for allocating medical groups to the casualties in different triage groups were developed to consider both groups simultaneously. We involve the treatment rate, the ratio of casualty groups, and the survival probability in the proposed strategies. The objective function was increased when more yellow casualties are treated, because the yellow group has a more survival probability. Therefore, we compare the strategies using the ratio of survivors to triaged people in both groups. This criterion was the summation of ratios of survivors to triaged people (RST) in two groups. The results show that the medical teams can be assigned to the casualty groups based on the saving rate. Here, there are some suggestions for future research. A new direction can be to consider the uncertainty in some parameters. In addition, other objective functions can also be introduced into a multi-objective model.

References

[1] Alinaghian, M., Goli, A., & Mokhatab Rafiei, F. (2015). Disaster relief vehicle routing with covering tour approach and fuzzy demands, solved by Hybrid Harmony Search Algorithm. *Advances in Industrial Engineering*, 49(1), 79-92.

[2] Alizadeh, M., Amiri-Aref, M., Mustafee, N., & Matilal, S. (2019). A robust stochastic Casualty Collection Points location problem, *European Journal of Operational Research*, 279, 3, 965-983.

[3] Baghaian, A., Lotfi, M.M. & Rezapour, S. (2022) Integrated deployment of local urban relief teams in the first hours after mass casualty incidents. *Operational Research International Journal*. https://doi.org/10.1007/s12351-022-00689-y

[4] Dean, MD. & Nair, SK. (2014). Mass-casualty triage: Distribution of victims to multiple hospitals using the SAVE model. *European Journal of Operational Research* 238(1), 363-373.

[5] Farahani RZ, Lotfi MM, Baghaian A, Ruiz R, Rezapour S (2020) Mass casualty management in disaster scene: A systematic review of OR&MS research in humanitarian operations. *European Journal of Operational Research* 287(3), 787–819.

[6] Feng, Y., Liu, T., Hu, Z., Wang, D., Cheng, T. C. E., & Yin, Y. (2021). Casualty transport scheduling considering survival probability and injury classification. *Computers & Industrial Engineering*, 161, 107655.

[7] Haeri, A., Reza, M., & Samani, G. (2020). A bi-level programming approach for improving relief logistics operations : A real case in Kermanshah earthquake. *Computers & Industrial Engineering*, *145*(July 2019), 106532.

[8] Hodgetts, T., & Macway-Jones, K. (1995). Major incident medical management and support. London: BMJ Publishing Group.

[9] Jin, S., Jeong, S., Kim, J., & Kim, K. (2014). A logistics model for the transport of disaster victims with various injuries and survival probabilities. *Annals of Operations Research*, 230 (1), 17–33.

[10] Kamali B, Bish D, & Glick R (2017). Optimal service order for mass-casualty incident response. E*uropean Journal of Operational Research* 261, 355-367.

[11] Lerner, E. B. , Schwartz, R. B. , Coule, P. L. , Weinstein, E. S. , Cone, D. C. , & Hunt, R. C. (2008). Mass casualty triage: An evaluation of the data and devel- opment of a proposed national guideline. *Disaster Medicine and Public Health Preparedness*, 2 (Supplement 1), S25–S34

[12] Li, Y., Zhang, J., & Yu, G. (2020). A scenario-based hybrid robust and stochastic approach for joint planning of relief logistics and casualty distribution considering secondary disasters. *Transportation Research Part E: Logistics and Transportation Review*, *141*(March), 102029.

[13] Liu Y, Cui N, & Zhang J (2019). Integrated temporary facility location and casualty allocation planning for post-disaster humanitarian medical service. *Transportation Research Part E: Logistics and Transportation Review* 128, 1–16.

[14] Lodree EJ, Altay N, & Cook RA (2019) Staff assignment policies for a mass casualty event queuing network. *Annals of Operations Research* 283(1), 411–442.

[15] Mills, A. F., Argon, N. T. , & Ziya, S. (2013). Resource-Based patient prioritization in mass-casualty incidents. *Manufacturing and Service Operations Management*, 15 (3), 361–377 .

[16] Oksuz, M.k., Satoglu, S.I., (2020). A two-stage stochastic model for location planning of temporary medical centers for disaster response. *International Journal of Disaster Risk Reduction*, 44, 101426.

[17] Rezapour, S., Baghaian, A., Naderi, N., & Farzaneh, M. A. (2022). Dynamic on-site treatment strategy for large-scale mass casualty incidents with rescue operation. *Computers & Industrial Engineering*, 163, 107796.

[18] Rezapour S, Naderi N, Morshedlou N, & Rezapourbehnagh S (2018) Optimal deployment of emergency resources in sudden onset disasters. *International Journal of Production Economics* 204, 365–382.

[19] Sabouhi, F., Bozorgi-Amiri, A., & Heydari, M. (2017). A Simultaneous Location, Routing and Scheduling Model for Transporting Evacuees with Time Window and Multiple Depots. *Advances in Industrial Engineering*, 51(2), 195-206.

[20] Sacco, W. J., Navin, D. M. , Fiedler, K. E. , Waddell, R. K. , Long, W. B. , & Buck- man, R. F. (2005). Precise formulation and evidence-based application of re- source-constrained triage. *Academic Emergency Medicine*, 12 (8), 759–770.

[21] Sun H, Wang Y, Zhang J, Cao W (2021a) A robust optimization model for location-transportation problem of disaster casualties with triage and uncertainty. *Expert Systems with Applications* 175, 114867.

[22] Sun H, Wang Y, & Xue Y (2021b) A bi-objective robust optimization model for disaster response planning under uncertainties. *Computers and Industrial Engineering* 155(99), 107213.

[23] Super, G., Groth, S., & Hook, R. (1994). START: Simple triage and rapid treatment plan . Newport Beach, CA: Hoag Memorial Presbyterian Hospital .

[24] Tirkolaee, E. B., Aydın, N. S., Ranjbar-Bourani, M., & Weber, G.-W. (2020). A robust bi-objective mathematical model for disaster rescue units allocation and scheduling with learning effect. *Computers & Industrial Engineering*, *149*, 106790.

[25] Zafari, F., Shishebori, D. (2019). Designing a Multi-Objective Three-Stage Location-Routing Model for Humanitarian Logistic Planning under Uncertainty. *Advances in Industrial Engineering*, 53(4), 149-167.

[26] Zhu, L., Gong, Y., Xu, Y., & Gu, J. (2019). Emergency relief routing models for in- jured victims considering equity and priority. *Annals of Operations Research*, 283 , 1573–1606.