Integrated optimization of facility location, casualty allocation and medical staff planning for post-disaster emergency response

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Abstract

Purpose – Disaster management and humanitarian logistics (HT) play crucial roles in large-scale events such as earthquakes, floods, hurricanes and tsunamis. Well-organized disaster response is crucial for effectively managing medical centres, staff allocation and casualty distribution during emergencies. To address this issue, this study aims to introduce a multi-objective stochastic programming model to enhance disaster preparedness and response, focusing on the critical first 72 h after earthquakes. The purpose is to optimize the allocation of resources, temporary medical centres and medical staff to save lives effectively.

Design/methodology/approach – This study uses stochastic programming-based dynamic modelling and a discrete-time Markov Chain to address uncertainty. The model considers potential road and hospital damage and distance limits and introduces an a-reliability level for untreated casualties. It divides the initial 72 h into four periods to capture earthquake dynamics.

Findings – Using a real case study in Istanbul's Kartal district, the model's effectiveness is demonstrated for earthquake scenarios. Key insights include optimal medical centre locations, required capacities, necessary medical staff and casualty allocation strategies, all vital for efficient disaster response within the critical first 72 h.

Originality/value – This study innovates by integrating stochastic programming and dynamic modelling to tackle post-disaster medical response. The use of a Markov Chain for uncertain health conditions and focus on the immediate aftermath of earthquakes offer practical value. By optimizing resource allocation amid uncertainties, the study contributes significantly to disaster management and HT research.

Keywords Humanitarian logistics, Disaster management, Emergency medical services, Casualty management, Facility location, Stochastic optimization

Paper type Research paper

1. Introduction

Emergency events database recorded 7,348 disasters worldwide, which affected more than four billion people, caused the loss of 1.2 million people's lives and resulted in economic losses of around US$2.97tn between the years 2000 and 2019. These numbers indicate not only the devastating effects of large-scale disasters but also the value of fostering greater awareness of the threat of disasters to take effective steps to protect lives. Humanitarian logistics (HT) and disaster management are globally significant due to the increasing frequency and severity of natural and man-made disasters, impacting communities, economies and human lives across borders. International collaboration, proactive preparedness, efficient response and innovative solutions are essential to address these challenges effectively in an interconnected world. The onset of the COVID-19 pandemic has further highlighted the existing deficiencies in disaster risk management, underscoring the necessity for a systematic and multi-hazard approach (Nandi, 2022). In recent years, despite the developments in disaster management and the increasing number of studies conducted for disaster preparedness and response, more studies are still needed to minimize risk and make more compatible and realistic plans.

Disaster management and HT consist of many activities such as preparation, relief supply distribution, casualty transportation, facility location, evacuation planning, network design and coordination. These are challenging processes and contain many uncertainties such as the time, location and severity of a disaster,

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number of casualties, demand for relief supplies and medical care and disruption to transportation networks and buildings. One of the most challenging processes is the emergency medical response to the casualties after mass casualty events (MCEs). This process contains the location of temporary medical centres (TMCs)/field hospitals, casualty triage and transportation, medical staff planning, emergency vehicle routing, etc.

Emergency medical services (EMS) play a crucial role in mitigating the severe impact of MCEs on casualties. By establishing a well-prepared and validated EMS system as part of emergency management, the morbidity and mortality associated with MCEs can be reduced. Alongside this, emergency medical centres (EMCs), which encompass hospitals and TMCs, hold a vital function in treating the injured and minimizing loss of life. While existing hospitals constitute a key component of post-disaster medical response, it is important to acknowledge that their capacity is often insufficient during MCEs. Consequently, the prompt setup of TMCs in appropriate locations immediately after a disaster becomes imperative to provide effective care for a large number of injured individuals. Hence, strategic planning for TMC locations and optimizing resource utilization becomes paramount to effectively respond to the needs of as many injured individuals as possible.

In the context of natural disasters, effective medical staff planning for medical centres is of utmost importance. Equally vital is the strategic planning of medical centre locations to ensure comprehensive services for all assigned casualties. Consequently, a well-thought-out approach involving the positioning of TMCs and the allocation of medical staff to these centres, considering expected casualties in disaster-stricken regions, becomes essential for a responsive and efficient casualty management system. It is crucial to note that not only the bed capacities of EMCs but also the availability of medical staff should be factored in when assigning casualties to these facilities. This comprehensive approach ensures that casualties receive appropriate and timely care within EMCs.

Although local and national governments have made efforts to respond promptly to disasters and make efficient use of resources, several studies indicate that disaster preparedness remains relatively low, even in areas prone to disasters (Altay and Green, 2006; Kohn *et al.*, 2012). In the literature, it is stated that because the resources available after the disaster are not sufficient for an effective response, the problems of both the location selection of medical centres and the casualty transportation are of great importance (Xiang *et al.*, 2009; Liu *et al.*, 2023). In addition, the importance of triage and TMCs to effectively use the limited medical resources and to mobilize these resources to save more patients is emphasized (Salman and Gül, 2014; Farahani *et al.*, 2020; Oksuz and Satoglu, 2020). Moreover, historical instances reveal that imbalances occurred, with excessive medical staff present in certain disaster-stricken regions while inadequate resources were available in others. Addressing this challenge necessitates a strategic allocation of medical personnel based on available resources, ensuring their efficient deployment to affected areas. This approach aims to rectify disparities and optimize the distribution of medical staff to disaster zones.

Assuming that all expected casualties occur immediately following a disaster can lead to inefficient utilization of EMC capacities, resulting in a lower-than-expected number of treated casualties. To address this concern, adopting a dynamic model that forecasts casualties over a designated time frame would enable more effective and practical use of EMC capacities. Natural disasters such as earthquakes, floods and hurricanes exhibit varying impacts on people over time. For instance, the initial 72 h post-earthquake are critical, with a significant influx of casualties in the initial 12 h. Consequently, estimating expected casualties should occur periodically within defined time frames. Moreover, it is imperative to assess each disaster type based on its unique characteristics and accordingly determine appropriate time segments. By doing so, optimal resource utilization (including medical centres, staff and supplies) can be achieved, ensuring timely responses to casualties.

This study explores the optimal location and number of TMCs, the distribution of casualties from disaster areas to EMCs and the required medical staff allocation to EMCs to effectively and promptly serve the affected population while considering various factors. The main goal is to reach as many injured people as possible in the aftermath of a disaster and thus save more lives. To achieve this objective, we have put forth a multi-objective stochastic model designed to address the dynamic challenges of TMC location planning, casualty allocation and medical staff assignment. The focal point of this endeavour is to minimize three critical factors:

1. the overall expected number of casualties left untreated;
2. the total expected demand weighted distance between disaster regions and EMCs; and
3. the cumulative expected number of required medical staff (comprising doctors and nurses) for the medical facilities.

The noteworthy contributions of this study are presented in the following:

- As far as our research indicates, no existing study in the available literature has explored the combined aspects of multi-period TMC location planning, casualty allocation and medical staff planning within an uncertain context.
- From the theoretical perspective, a novel multi-objective dynamic stochastic optimization model was developed for the addressed problem.
- In addition, α-reliability levels (chance constraints) were first described for the problem and used in the model.
- Discrete-time Markov Chain approach was applied in the model to reflect the stochastic nature of the casualties' health condition.
- From the practical perspective, the capacities of medical centres are divided into bed and outpatient care capacity to be realistic.
- The possibilities for road and hospital damage are considered.
- Distance limit constraints were used to ensure that immediate casualties were not assigned to hospitals located far away.
- The capacities of the medical centres are updated dynamically according to the assigned casualties in each period.
- From the managerial point of view, several strategic and operational decisions are provided regarding the required number and optimal locations of TMCs, additional capacity needs, the necessary medical staff and the optimal allocation of casualties.

To validate our proposed model, a practical case study was conducted in the Kartal district of Istanbul, recognized as one of the most vulnerable areas in the event of a potential earthquake. To estimate the number of casualties in each sub-district, we referred to the "Possible Earthquake Loss Estimate Booklets" (IBB-KRDAE, 2020). For solving the multi-objective model within this case study, we used the AUGMECON2 method (Mavrotas and Florios, 2013) and subsequently analysed the obtained results. The examination of these case study outcomes has yielded valuable managerial insights regarding the optimal number and placement of TMCs, the required medical staff and the distribution of casualties.

The structure of the paper is outlined as follows: Section 2 offers an extensive examination of the existing literature on HT. Section 3 elaborates on the methodology, encompassing the definition of the problem, model formulation and the methodology used for finding solutions. Sections 4 and 5 delve into the case study and computational results, respectively. To conclude, the paper presents the conclusions and significant findings.

2. Literature review

The increasing need for efficient allocation of scarce resources highlights the importance of operations research (OR) as a vital discipline, offering tools to enhance relief and development operations within HT (Van Wassenhove and Pedraza Martinez, 2012). The HT or disaster management operations consist of many problems such as facility location, inventory management, relief distribution, casualty transportation/allocation, emergency vehicle routing, evacuation and medical staff planning. The number of academic studies on these topics has increased rapidly in the past decades. Farahani *et al.* (2020) undertook an extensive review of existing literature in the field of HT and put forth prospective avenues for future research across various problem domains. As indicated in their review, there remains an unmet requirement for pragmatic and true-to-life investigations concentrating on diverse facets of disaster management.

Different disaster types possess distinct characteristics that necessitate tailored preparedness and response strategies. Earthquakes, for instance, strike suddenly and without warning, causing building collapses and structural damage. Floods, on the other hand, result from heavy rainfall or storm surges, affecting large areas and leading to widespread displacement. Hurricanes and typhoons, with predictable paths, bring powerful winds and flooding. Wildfires are characterized by rapid, unpredictable spread in dry, windy conditions, whereas tornadoes are violently rotating columns of air with limited predictability. Volcanic eruptions vary in size and impact, unleashing lava flows, ash clouds and pyroclastic flows. Pandemics, such as COVID-19, disrupt global systems with rapid and widespread infectious transmission. Man-made disasters such as terrorism, war and biological/chemical threats require complex humanitarian responses to address both immediate and long-term consequences. Understanding these characteristics of disasters is pivotal for effective disaster management and HT.

Right after an MCE such as a disaster, we may be faced with many casualties in a very short period. These casualties require immediate care, and their life depends on a quick response. Therefore, managing the EMS system and resources is crucial in the first few hours of a disaster, and a successful emergency medical response will significantly increase the survival rate of the casualties. The morbidity and mortality associated with the MCEs can be decreased by providing a well-planned EMS system. The most critical problems for the EMS after a disaster are TMC/field hospital location planning, casualty transportation/allocation, emergency vehicle routing and medical staff assignment.

In Table 1, the studies considered these problems are presented and classified according to different categories. Even if these problems are related to each other, the studies have generally focused on one or two of them in the proposed models. A limited number of studies consider the medical staff assignment problem for the post-disaster emergency medical response. Furthermore, it is worth noting that there is currently no existing study in the available literature that simultaneously addresses the interconnected challenges of facility location, casualty allocation and medical staff assignment problems. Because these problems are related to each other, it is important to consider them simultaneously.

According to the objective function, coverage is the most used criterion in the studies. Coverage is defined differently, such as minimizing untreated casualties or unmet demand, maximizing treated/assigned casualties or total lifesaving and demand satisfaction. Cost is the second most used objective in the models. It is the most critical factor in traditional supply chains but is also used in humanitarian supply chains. However, in some studies, it was argued that saving human life, namely, maximizing the number of people reached (coverage) or minimizing unmet demand, should take priority over other purposes (Turkeš *et al.*, 2019). On the other hand, in some problems, there has been a necessity to consider the cost in the objective functions such as transportation cost of casualties, setup cost of TMCs or penalty costs. Another fact is having limited resources such as budget, vehicles and relief supplies. Response time and distance are similar objective functions considered in the EMS studies. Distance is sometimes defined as response time by considering the transportation time of casualties. For more information on the objective functions, readers should refer to the papers of Holguín-Veras *et al.* (2013) and Turkeš *et al.* (2019) that analysed the objectives used in the humanitarian logistic models. Holguín-Veras *et al.* (2013) suggested using social costs, including logistics costs and deprivation costs of the victims' suffering. Turkeš *et al.* (2019) suggested using the minimization of unmet demand in the objective function instead of cost.

In the literature, the time horizon is mostly considered as a single period. It means that decisions are made one-off and do not change over time. Because available treatment resources such as bed capacity and available medical staff of EMCs are limited and change over time, the decisions must be made dynamically by considering a multi-period, especially for the first 72 h. Besides, the demand for medical care for casualties differs in time after the disaster. For example, in the aftermath of an earthquake, most of the demand occurs in the first 12 h,

Table 1 Classification of the relevant studies

		Problem type				Objective function			Time horizon		Uncertainty	
Author	**Year**	**Facility location**	**Casualty allocation**	**Medical staff assignment**	**Response time**	**Distance**	**Cost**	**Coverage**	**Single-period**	**Multi-period**	**Deterministic**	**Stochastic**
Jia *et al.*	2007	*				*		*	*		*	
Salmerón and Apte	2010	*	*					*	*			*
Özdamar and Demir	2012		*		*				*		*	
Toro-Díaz *et al.*	2013	*	*		*			*	*			*
Wilson *et al.*	2013		*		*			*		*		*
Salman and Gül	2014	*	*		*		*			*	*	
Lodree *et al.*	2014			*			*			*		*
Repoussis *et al.*	2016		*		*				*		*	
Shahriari *et al.*	2017		*			*		*	*		*	
Caunhye and Nie	2018	*	*					*	*			*
Niessner *et al.*	2018		*	*	*			*		*		*
Gu *et al.*	2018	*	*					*	*		*	
Mills *et al.*	2018		*					*	*			*
Pouraliakbarimamaghani *et al.*	2018	*	*			*		*	*		*	
Wang *et al.*	2019	*	*			*	*	*		*	*	
Liu *et al.*	2019	*	*				*	*	*		*	
Shavarani *et al.*	2019		*	*		*		*		*		*
Ghasemi *et al.*	2020	*	*				*	*		*		*
Oksuz and Satoglu	2020	*	*				*		*			*
Adarang *et al.*	2020	*	*		*		*		*		*	
Sun *et al.*	2021	*	*				*	*	*			*
Ghasemi *et al.*	2022	*	*		*		*		*			*
Chang *et al.*	2023	*	*		*	*			*			*
This paper		*	*	*		*	*	*		*		*

Note: *Valid feature of the study
Source: Table created by authors

and it continues to decrease as time passes. On the other hand, this demand cannot be precisely determined in advance. However, in deterministic studies, the demand and other uncertain parameters are estimated in some cases and used to test the proposed models. The authors mostly used stochastic programming models to consider uncertainty by defining different scenarios for possible disasters. In the following sub-sections, we further classified and discussed the studies.

2.1 Facility location

The domain of facility location studies is primarily concerned with spatial aspects of operations, investigating how facilities impact factors such as costs, services and response times. Within the HL literature, these studies can be generally categorized into three main groups: relief supplies warehouses, shelter sites/collection points and the location of TMCs/field hospitals. These inquiries frequently factor in elements such as response times to demand, distances between disaster-affected zones and relief/medical centres, transportation expenses and the level of demand satisfaction when determining suitable locations. Additionally, some facility location studies take equity and fairness into consideration, aiming to ensure a balanced distribution of relief supplies to all demand points or to provide a timely and equitable response to casualties. This equitable approach is often reflected in objective functions that strive to minimize parameters such as the maximum distance between demand points and facilities (Jia *et al.*, 2007; Huang *et al.*, 2010) or the maximum response time to any demand point (Lu *et al.*, 2013). Furthermore, Erbeyoğlu and Bilge (2020) introduced a fairness perspective by defining specific time frames and fulfilling a predetermined portion of demand within each frame.

Within the literature, the location challenges of relief supplies warehouses, shelters and casualty collection points (CCPs) have been frequently explored. Conversely, the problem of determining optimal locations for TMCs has been the subject of a relatively smaller number of investigations. Ahmadi-Javid *et al.* (2017) highlighted the scarcity of studies using stochastic programming and robust optimization techniques for medical centre location problems. Jia *et al.* (2007) introduced a stochastic p-median model aimed at determining optimal medical centre locations. Their approach accounted for demand uncertainty, facility damage probabilities and capacity fluctuations. This model's efficacy was evaluated across various potential disaster scenarios in Seattle. Aydin (2016) proposed a stochastic p-median model cantered around establishing field hospital locations for potential earthquakes in Istanbul's Zeytinburnu district. The model also incorporated the possibility of existing hospitals being rendered non-functional. Fereiduni and Shahanaghi (2017) presented a single-objective mathematical model to address a broader network design problem encompassing TMC locations, relief supply distribution and evacuation considerations. This model sought to minimize overall transportation, inventory holding and facility setup costs. Liu *et al.* (2019) took a comprehensive approach by integrating both TMC location and casualty allocation concerns. Their model aimed to maximize expected survivals while minimizing operational expenses. This deterministic bi-objective model was solved using the ε-constraint method.

Oksuz and Satoglu proposed a two-stage stochastic programming model for location planning of TMCs and transportation of casualties. It is aimed at minimizing the total setup cost of TMCs and the expected total transportation cost of casualties. A real case study was conducted for possible earthquake scenarios, and sensitivity analysis was made for important parameters. Adarang *et al.* (2020) introduced a bi-objective mixed-integer programming framework addressing the location-routing predicament, which encompassed hospitals, TMCs and emergency vehicles, including ambulances and helicopters. Their model pursued two primary objectives: firstly, it aimed to minimize relief time, and secondly, it sought to minimize the cumulative location cost for TMCs and transfer points, along with the routing expenses for vehicles. Ghasemi *et al.* (2020) proposed a multi-objective stochastic programming model for location planning of relief distribution and TMCs and allocating vehicles and relief commodities. A simulation model was used to determine the demand for relief commodities, including water, food, blood, blankets and tents. A real case study was conducted for possible earthquake scenarios expected to occur in Tehran. The proposed model was solved using an epsilon-constraint approach and a non-dominated sorting genetic algorithm (NSGA-II).

Sun *et al.* (2021) proposed a bi-objective robust optimization model for facility location, resource allocation and casualty transportation in a three-level rescue chain. The model uses the injury severity score (ISS) for casualty categorization and accounts for uncertainties in demand and transportation time. The aim is to minimize both total ISS and system costs, using penalty coefficients for untransported casualties and unmet relief supplies. The robust optimization method and the ε-constraint method are used to develop and solve the model, respectively. Turkeš *et al.* (2022) analysed the impact of various factors and their interactions on facility location decisions for inventory pre-positioning in emergency preparedness. They carried out an experimental study to determine key factors in decision-making and to provide robust guidelines that can be applied across different disasters in the context of HT. Chang *et al.* (2023) focused on optimizing CCP locations and allocating EMS resources to enhance casualty survival rates in mass casualty incidents (MCI). They use a hybrid simulation-optimization approach, considering the stochastic and dynamic nature of MCI logistics and develop a novel two-stage sequential algorithm. They applied their algorithm to a potential earthquake scenario in Tainan City and investigated the influence of different resource levels and road damage degrees on location-allocation decisions and expected delivery times. Recently, Liu *et al.* (2023) considered the location of EMCs in megacities for public health emergencies. The authors proposed a genetic algorithm for this problem and conducted a case study for Guangzhou city of China. Chang *et al.* (2023) considered the CCP location and resource allocation problem by investigating the impact of varying degrees of scarce emergency medical resources and road damage on the expected total delivery time of all casualties and the location-allocation. The authors proposed a simulation-optimization methodology for this problem and conducted a sensitivity analysis.

2.2 Casualty allocation/transportation

Casualty transportation, encompassing the evacuation and transfer of injured individuals from affected regions to EMCs, stands out as a pivotal undertaking in disaster response (Safeer *et al.*, 2014). In studies related to casualty transportation, a predominant approach involves the minimization of distances and transportation durations (Horner and Widener, 2011; Wilson *et al.*, 2013; Yi and Kumar, 2007) or the maximization of service levels and the number of treated casualties in the objective functions (Feng and Wang, 2003; Yi and Özdamar, 2007). Moreover, a subset of these studies focuses on casualty transportation via specialized emergency vehicles like ambulances and helicopters. In this context, Barbarosoğlu *et al.* (2002) directed their attention to helicopter-based casualty transportation, with the principal objective being the minimization of the number of helicopter trips needed.

In certain research studies, there is a concurrent consideration of both facility location and challenges related to casualty transportation or medical supplies distribution. Salmerón and Apte (2010) developed a two-stage stochastic programming model that encompassed the location of warehouses, medical centres, ramp areas and shelters. This model also accounted for the distribution of materials and the transportation of casualties. Özdamar and Demir (2012) introduced a hierarchical clustering and network design model designed to transport casualties from disaster zones to EMCs and to distribute aid supplies to those casualties. Their model aimed to minimize the overall estimated transportation time, thus optimizing vehicle utilization. Toro-Díaz *et al.* (2013) presented a nonlinear mixed-integer stochastic programming model that simultaneously addressed ambulance distribution and location challenges. They used a genetic algorithm to solve this model, considering fairness by minimizing the variance of individual response times to casualties. The model's objectives included either response time minimization or maximum coverage, with the authors noting that better results were achieved by prioritizing response time minimization.

Salman and Gül (2014) introduced a multi-period mathematical model that addresses the identification of optimal locations for new TMCs to be established. This model encompasses the determination of centre capacities at the commencement of each period, along with the relocation of casualties to these centres. The primary objective of this model is the minimization of cumulative transportation and waiting times for casualties, as well as the total setup cost associated with the new facilities. Rath *et al.* (2016) developed a two-stage stochastic programming model to determine the locations of warehouses and the allocation of vehicles in the transportation system for delivering aid supplies. They compared a heterogeneous vehicle fleet to a homogeneous fleet to analyse the impacts on the solution. Repoussis *et al.* (2016) introduced a mixed-integer programming model that simultaneously addresses ambulance dispatching, casualty allocation and treatment sequencing. The model's objectives are twofold: the minimization of both the aggregate response time and the total flow time required for all casualties. To evaluate their model, a hypothetical scenario involving a terror attack was used as a testing case. Shahriari *et al.* (2017) proposed a bi-objective mixed-integer programming framework that revolves around the location planning of ground and air ambulance bases, as well as helipads. Additionally, the transportation of casualties for emergency medical response was incorporated into their model. It aims to minimize travel time and maximize service level by considering the demand uncertainty. A case study was conducted for Lorestan in Iran for an MCE, and a sensitivity analysis was made for different parameters.

Gu *et al.* (2018) devised a mixed-integer programming model targeting the location planning of TMCs, the allocation of casualties to these centres and the distribution of medical supplies, all within a constrained budget. Their primary objective was to maximize the count of treated casualties. They also proposed a greedy algorithm tailored for handling large-scale instances of the problem. Caunhye and Nie (2018) examined the casualty allocation issue from a distinct angle by considering the movements of self-evacuees. They put forth a three-stage stochastic model that addressed the location of alternate medical centres alongside the allocation of casualties. To solve this problem, the authors introduced a Benders decomposition-based algorithm in addition to a two-stage approximation model. Mills *et al.* (2018) studied the casualty transportation problem, including allocating ambulances to patient locations and transporting the patients to the medical centres after the disaster, by simulation. Alizadeh *et al.* (2019) proposed a multi-period robust stochastic optimization model for the casualty allocation and location problem. The number of casualties and the transportation capacity were considered uncertain parameters. A computational study was made for a hypothetical case of a gas leak in Bhopal, India. Caglayan and Satoglu (2021) developed a multi-objective two-stage stochastic programming model to minimize the number of untransported casualties, additional ambulance requirements and total transportation time. The proposed model was applied to a district in Istanbul, Turkey, in the context of a major earthquake. The study highlights the importance of a data-driven decision support tool for directing ambulances based on hospital capacity availability.

Ghasemi *et al.* (2022) focused on earthquake preparedness and response planning by proposing a scenario-based stochastic multi-objective location-allocation-routing model that simultaneously considers pre- and post-disaster. The model aims to minimize total relief supply chain costs, unsatisfied demands for relief staff and the probability of unsuccessful evacuations. The model is solved using the epsilon-constraint method and three metaheuristic algorithms for different problem scales. Recently, Babaqi and Vizvari (2023) investigated the casualty transportation problem for post-disaster emergency response. The transportation of casualties by ambulances to hospitals is considered by defining a deadline for transferring casualties to the hospital. They proposed an integrated approach using a mathematical model and heuristics for this problem.

2.3 Medical staff planning/assignment studies in humanitarian logistics

The medical staff assignment problem within the context of emergency response has received comparatively less attention in the literature despite its paramount importance in ensuring adequate medical care during casualty transportation. Various aspects of this problem have been explored in existing literature. Lodree *et al.* (2019) proposed a queueing network framework for efficiently allocating medical staff (both doctors and nurses) to different classes of casualties, aiming to effectively manage the abrupt surge in medical response demand. They modelled the queueing network as a stochastic dynamic programming challenge with a finite horizon in discrete time. In their study, three heuristic policies were devised, and they also accounted for heterogeneous team collaboration, combining doctors and nurses to handle immediate casualties effectively.

In recent studies, Niessner *et al.* (2018) presented three simulation-optimization models that address the dynamic allocation of medical staff (including physicians and medics) to field hospitals. The overarching goal of these models was to minimize rescue time and the count of deceased patients. The authors tested their proposed models using a gas explosion scenario and explored various policies to enhance their applicability. Pouraliakbarimamaghani *et al.* (2018) introduced a multi-objective integer programming model for the strategic placement of TMCs near hospitals alongside the allocation of casualties. This approach took into account both the medical staff and bed capacity of hospitals. The authors applied NSGA-II and a non-dominated ranking genetic algorithm to solve this complex problem across 15 hypothetical cases. Shavarani *et al.* (2019) devised a bi-objective mixed-integer nonlinear model tailored to the assignment of medical staff (comprising surgeons and anaesthetists) to operating rooms within hospitals during MCEs. Their model sought to minimize both the expected number of functioning operating rooms and the anticipated distance between critically injured individuals and suitable operating rooms. For a potential earthquake scenario in Tehran, the authors proposed using simulated annealing, genetic algorithms and particle swarm optimization algorithms, with objectives weighted to strike a balance between the two goals. Recently, Ahadian *et al.* (2023) considered the allocation of medical staff to prevent a shortage of hospital beds for the management of pandemic waves. The authors proposed a mixed-integer linear programming model for this problem by considering several performance ratios such as the ratio of hospitalized patients to the specialized personnel assigned to each hospital.

Summing up the review, it becomes evident that the issues related to location planning of TMCs, casualty transportation and medical staff assignment under uncertain conditions have been explored with relatively limited attention in the existing literature. Moreover, the notable observation is that no study has been conducted to address these interconnected problems simultaneously. Despite the importance of emergency medical response planning for casualty management, this subject has received relatively less attention in the literature (Gupta *et al.*, 2016). Farahani *et al.* (2020) also stated the need for integrated and multi-period planning of the EMS and consideration of the dynamic behaviour of casualties' health conditions and suggested these issues for future research. In light of these observations, our proposed model stands to significantly contribute to the HT literature by addressing an important gap in research that has not been adequately explored thus far.

3. Problem definition and stochastic model

The most frequently used optimization approach is deterministic programming, where all parameters are assumed to be known with certainty. It does not account for uncertainty and is used when the problem is entirely deterministic. However, stochastic programming deals with optimization problems involving uncertainty or randomness in decision-making. It is used when the parameters of a model are not known with certainty due to the probabilistic nature of the problem by considering different scenarios and their probabilities. On the other hand, dynamic modelling deals with problems where decisions evolve, and optimization involves a sequence of decisions made at different periods (Puterman, 2014). It is commonly used in problems with a temporal aspect, such as supply chain logistics, project management and resource allocation over time. Dynamic modelling often uses dynamic programming, Markov decision processes and control theory to optimize decisions over time (Yaesoubi and Cohen, 2011). The objective of dynamic modelling is to find a policy or strategy that maximizes or minimizes an objective function over a specified time horizon while considering dynamic constraints.

In the following, we first present the problem's definition, which includes an explanation of the emergency medical response system's network structure. We then delve into the description of the Markov Chains, illustrating the progression of health conditions for both treated and untreated casualties. Moving forward, we outline the specifics of the multi-objective stochastic model. Subsequently, we provide a detailed account of the solution methodology, using the AUGMECON2 approach.

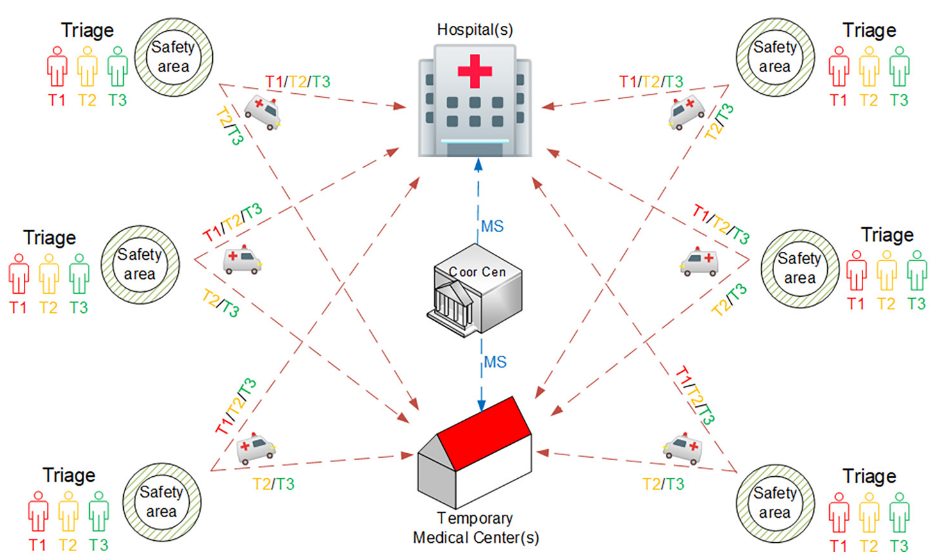
3.1 Problem definition

The configuration of the post-disaster emergency medical response system, which is the focal point of this study, is illustrated in Figure 1. In this proposed system, immediate casualties (T1) are exclusively transferred to hospitals due to their requirement for advanced medical care beyond the capabilities of TMCs. For delayed and minimal casualties, the option exists for them to be transported to either TMCs or hospitals. The assumption is made that the medical staff conducts triage classification within safe zones after the disaster event. Our consideration involves a medical staff composed of a doctor and a nurse, who cater to the number of casualties assigned to EMCs to ensure comprehensive care provision. For this reason, we establish a defined maximum threshold for the number of casualties that a doctor and nurse can effectively attend to within a given timeframe. The service duration for each casualty category (T1, T2 and T3) is determined based on expert input. Additionally, it assumed that an adequate medical staff is allocated to EMCs from a coordinating centre in alignment with the requirements.

To capture the dynamic nature of such incidents, we introduced a multi-period approach and focused on planning for the initial 72 h following the disaster, according to the recommendation made by Russell *et al.* (1995). This time frame was divided into four distinct periods: 0–12 h, 12–24 h, 24–48 h and 48–72 h. Each period was assigned a predefined casualty rate, denoting the proportion of the total expected casualties for that specific period. These casualty rates were established based on the findings of Rawls and Turnquist (2012), who conducted a study concerning the dynamic allocation of emergency supplies amid uncertainty to meet all demands within disaster-affected regions.

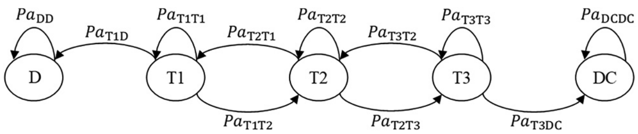
We incorporated the inherent uncertainty of casualties' health conditions into the model using a discrete-time Markov Chain framework, similar to the approaches followed by Saoud *et al.* (2006) and Wilson *et al.* (2013). This scheme delineates three distinct states to capture the health condition of a casualty, namely, healing, deterioration and stable states. In the case of treated casualties, all three states of healing, deterioration and stability are considered, as depicted in Figure 2. For untreated casualties, the consideration extends to only the deterioration and stable states, as represented in Figure 3. To characterize the transition probabilities of the casualties' health conditions, two transition matrices are used.

Figure 1 Network design of post-disaster emergency medical response system



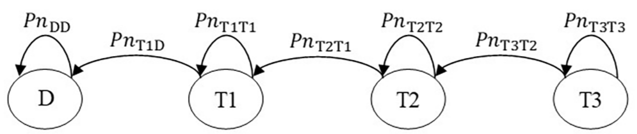
Source: Figure adapted from Oksuz and Satoglu (2020)

Figure 2 The Markov Chain illustrating the health condition transitions for treated casualties (D: dead, DC: discharged)



Source: Figure created by authors

Figure 3 The Markov Chain illustrating the health condition transitions for untreated casualties



Source: Figure created by authors

Expanding upon the existing triage classifications for casualties, we introduced two additional categories: "discharged" and "dead." In each successive period, the capacity of EMCs is adjusted based on the probabilities of casualties being discharged (DC) or deceased (D). Furthermore, untreated casualties from preceding periods are carried over to subsequent periods. Concurrently, the EMC capacity is categorized into two distinct classes: bed capacity and outpatient care capacity. Specifically, bed capacity is reserved for casualties of types T1 and T2, whereas outpatient care capacity accommodates casualties of type T3. The dynamics inherent in these events are accounted for periodically, encompassing the fluctuation in anticipated casualty numbers and the practical capacities of EMCs over time.

3.2 Stochastic model

We formulated a multi-objective dynamic stochastic programming model to address the challenges of TMC location, casualty allocation and medical staff assignment in extensive emergency scenarios. The subsequent sections outline the sets and indices, parameters and decision variables integral to the model's structure and formulation.

Sets and indices:

I, i = set and index of demand points, $i \in I$;
$\mathcal{J}, j$ = set and index of EMCs (hospitals + TMCs), $j \in \mathcal{J}$;
$\mathcal{J}_H$ = set of existing hospitals;
$\mathcal{J}_T$ = set of TMCs;
S, s = set and index of possible scenarios, $s \in S$;
P, p = set and index of periods, $p \in P$;
t = classification of casualties following triage, $t = T1, T2$ or $T3$; and
k = capacity category of EMCs (for bed capacity $k = 1$, for outpatient care capacity $k = 2$).

Parameters:

P_s = probability of scenario-s occurrence;
d_{ij} = distance between demand point-i and EMC-j;
D_L = distance limit for assigning type-T1 (immediate) casualties from location-i to EMC-j;
Cap_{jk} = initial quantity of capacity of type-k available at EMC-j before the occurrence of the disaster;
M = a large positive number;
f_{ij}^{s} = ratio of the increment in distance on road i–j under scenario-s;
g_j^{s} = ratio of the decrease in capacity for hospital-j in scenario-s;
$T1_{ip}^{s}$ = number of immediate casualties at demand point-i during period-p of scenario-s;
$T2_{ip}^{s}$ = number of delayed casualties at demand point-i during period-p of scenario-s;
$T3_{ip}^{s}$ = number of minimal casualties at demand point-i during period-p of scenario-s;
α = reliability level;
D_j = initial number of available doctors at hospital-j;
N_j = initial number of available nurses at hospital-j;
θ_t^{ps} = max. number of type-t casualties that a doctor can treat during period-p of scenario-s;
γ_t^{ps} = max. number of type-t casualties that a nurse can treat during period-p of scenario-s;
P_{att} = the transition probability of the health condition of treated casualties ($t = T1, T2$ or $T3$); and
Pn_{tt} = the transition probability of the health condition of untreated casualties ($t = T1, T2$ or $T3$).

Decision variables:

T_{ijt}^{ps} = number of type-t casualties in demand point-i and assigned to EMC-j in period-p of scenario-s;
Non_{it}^{ps} = number of untreated type-t casualties in demand point-i in period-p of scenario-s;
Cap_{jk}^{ps} = available capacity of type-k of EMC-j in period-p of scenario-s;
De_j^{ps} = number of additional doctors required at hospital-j in period-p of scenario-s;
Ne_j^{ps} = number of additional nurses required at hospital-j in period-p of scenario-s;
Dt_j^{ps} = number of doctors to assign to TMC-j in period-p of scenario-s;
Nt_j^{ps} = number of nurses to assign to TMC-j in period-p of scenario-s;
X_{ijT1}^{ps} = 1, if EMC-j serves immediate casualties in demand point-i in scenario-s; and 0, otherwise; and
δ_s = 1, if all casualties can be assigned to EMCs in scenario-s; and 0, otherwise.

Model formulation:

Objective-1:

$$Min \sum_{s \in S} P_s \sum_{p \in P} \sum_{t \in T} \sum_{i \in I} Non_{it}^{ps} \tag{1.1}$$

Objective-2:

$$Min \sum_{s \in S} P_s \sum_{i \in I} \sum_{j \in \mathcal{J}} \sum_{t \in T} \sum_{p \in P} d_{ij} \left(1 + f_{ij}^{s}\right) T_{ijt}^{ps} \tag{1.2}$$

Objective-3:

$$Min \sum_{s \in S} P_s \left(\sum_{p \in P} \sum_{j \in \mathcal{J}_H} De_j^{ps} + Ne_j^{ps} + \sum_{p \in P} \sum_{j \in \mathcal{J}_T} Nt_j^{ps} + Dt_j^{ps} \right) \tag{1.3}$$

Subject to

Capacity constraints for assigned casualties:

$$\sum_{i\in I}\sum_{t\in T1,T2}T_{ijt}^{ps} \leq Cap_{j1}^{ps} \qquad (\forall j \in \mathcal{J}_H), (\forall p \in P), (\forall s \in S) \tag{2}$$

$$\sum_{i\in I}T_{ijT2}^{ps} \leq Cap_{j1}^{ps} \qquad (\forall j \in \mathcal{J}_T), (\forall p \in P), (\forall s \in S) \tag{3}$$

$$\sum_{i\in I}T_{ijT3}^{ps} \leq Cap_{j2}^{ps} \qquad (\forall j \in \mathcal{J}), (\forall p \in P), (\forall s \in S) \tag{4}$$

Capacity updating through the periods:

For pre-disaster ($p=P0$);

$$Cap_{jk}^{0s} = Cap_{jk} \qquad (\forall j \in \mathcal{J}), (\forall k \in K), (\forall s \in S) \tag{5}$$

For post-disaster ($p=P1$):

$$Cap_{jk}^{1s} = Cap_{jk}^{0s}\left(1-g_j^s\right) \qquad (\forall j \in \mathcal{J}), (\forall k \in K), (\forall s \in S) \tag{6}$$

$$Cap_{jk}^{ps} = Cap_{jk}^{p-1,s} - \sum_{i\in I}\sum_{t\in T1,T2}T_{ijt}^{p-1,s} + \sum_{i\in I}T_{ijT1}^{p-1,s}Pa_{T1D} + \sum_{i\in I}T_{ijT2}^{p-1,s}Pa_{T2T3} \tag{7}$$

$$(\forall k \in K1), (\forall j \in \mathcal{J}_H), \ (\forall p \in P2, P3, P4), (\forall s \in S)$$

$$Cap_{jk}^{ps} = Cap_{jk}^{p-1,s} - \sum_{i\in I}T_{ijT2}^{p-1,s} + \sum_{i\in I}T_{ijT2}^{p-1,s}Pa_{T2T3} \tag{8}$$

$$(\forall k \in K1), (\forall j \in \mathcal{J}_T), \ (\forall p \in P2, P3, P4), (\forall s \in S)$$

$$Cap_{jk}^{ps} = Cap_{jk}^{p-1,s} - \sum_{i\in I}T_{ijT3}^{p-1,s} + \sum_{i\in I}T_{ijT3}^{p-1,s}Pa_{T3Dc} \tag{9}$$

$$(\forall k \in K2), (\forall j \in \mathcal{J}), \ (\forall p \in P2, P3, P4), (\forall s \in S)$$

Casualty assignment (demand) constraints:

$$\sum_{j\in \mathcal{J}_H}T_{ijT1}^{ps} + Non_{iT1}^{ps} = T1_{ip}^{s} \qquad (\forall i \in I), (\forall p \in P1), (\forall s \in S) \tag{10}$$

$$\sum_{j\in \mathcal{J}}T_{ijT2}^{ps} + Non_{iT2}^{ps} = T2_{ip}^{s} \qquad (\forall i \in I), (\forall p \in P1), (\forall s \in S) \tag{11}$$

$$\sum_{j\in \mathcal{J}}T_{ijT3}^{ps} + Non_{iT3}^{ps} = T3_{ip}^{s} \qquad (\forall i \in I), (\forall p \in P1), (\forall s \in S) \tag{12}$$

$$\sum_{j\in \mathcal{J}_H}T_{ijT1}^{ps} + Non_{iT1}^{ps} = T1_{ip}^{s} + Non_{iT1}^{p-1,s}Pn_{T1T1} + Non_{iT2}^{p-1,s}Pn_{T2T1} - Non_{iT1}^{p-1,s}Pn_{T1D} \tag{13}$$

$$(\forall i \in I), (\forall p \in P2, P3, P4), (\forall s \in S)$$

$$\sum_{j\in \mathcal{J}}T_{ijT2}^{ps} + Non_{iT2}^{ps} = T2_{ip}^{s} + Non_{iT2}^{p-1,s}Pn_{T2T2} + Non_{iT3}^{p-1,s}Pn_{T3T2} - Non_{iT2}^{p-1,s}Pn_{T2T1} \tag{14}$$

$$(\forall i \in I), (\forall p \in P2, P3, P4), (\forall s \in S)$$

$$\sum_{j\in \mathcal{J}}T_{ijT3}^{ps} + Non_{iT3}^{ps} = T3_{ip}^{s} + Non_{iT3}^{p-1,s}Pn_{T3T3}; \quad (\forall i \in I), (\forall p \in P2, P3, P4), (\forall \in S) \tag{15}$$

Distance limit for immediate casualties ($T1$):

$$d_{ij}\left(1+f_{ij}^{s}\right)X_{ijT1}^{ps} \leq D_L, \qquad (\forall i \in I), (\forall j \in \mathcal{J}_H), (\forall s \in S)(\forall p \in P) \tag{16}$$

Assignment constraints for immediate casualties ($T1$):

$$T_{ijT1}^{ps} \leq X_{ijT1}^{ps}M \quad (\forall i \in I), (\forall j \in \mathcal{J}), (\forall p \in P), (\forall s \in S) \tag{17}$$

$$T_{ijT1}^{ps} \geq X_{ijT1}^{ps} \qquad (\forall i \in I), (\forall j \in \mathcal{J}), (\forall p \in P), (\forall s \in S) \tag{18}$$

Medical staff assignment constraints:

$$\sum_{i\in I}T_{ijT2}^{ps} \ / \ \theta_{T2}^{ps} \leq Dt_j^{ps} \quad (\forall j \in \mathcal{J}_T), (\forall p \in P), (\forall s \in S) \tag{19}$$

$$\sum_{i\in I}\sum_{t\in T2,T3}T_{ijt}^{ps} \ / \ \gamma_t^{ps} \leq Nt_j^{ps} \quad (\forall j \in \mathcal{J}_T), (\forall p \in P), (\forall s \in S) \tag{20}$$

$$\sum_{i\in I}\sum_{t\in T1,T2}T_{ijt}^{ps} \ / \ \theta_t^{ps} \leq D_j^{ps} + De_j^{ps} \quad (\forall j \in \mathcal{J}_H), (\forall p \in P), (\forall s \in S) \tag{21}$$

$$\sum_{i\in I}\sum_{t\in T}T_{ijt}^{ps} \ / \ \gamma_t^{ps} \leq N_j^{ps} + Ne_j^{ps} \quad (\forall j \in \mathcal{J}_H), (\forall p \in P), (\forall s \in S) \tag{22}$$

α-reliability (chance-constraints):

$$\sum_{s\in S}P_s\delta_s \geq \alpha \tag{23}$$

$$\sum_{i\in I}Non_{it}^{ps} \leq M(1-\delta_s) \qquad (\forall p \in P), \ (\forall s \in S)(\forall t \in T) \tag{24}$$

$$\sum_{i\in I}Non_{it}^{ps} \geq (1-\delta_s) \qquad (\forall p \in P), \ (\forall s \in S)(\forall t \in T) \tag{25}$$

Binary and positive variables:

$$X_{ijT1}^{ps}, \ \ \delta_s \in \{0,1\}, \qquad (\forall i \in I), (\forall j \in \mathcal{J}), \ (\forall p \in P)(\forall s \in S) \tag{26}$$

$$T_{ijt}^{ps}, \quad Non_{it}^{ps}, De_j^{ps}, Ne_j^{ps}, Dt_j^{ps}, Nt_j^{ps} \geq 0 \quad \text{and} \quad \text{integer}, \tag{27}$$

$$(\forall i \in I), (\forall j \in \mathcal{J}), (\forall t \in T), (\forall p \in P), (\forall s \in S)$$

$$Cap_{jk}^{ps} \geq 0, \qquad (\forall j \in \mathcal{J}), (\forall k \in K), (\forall p \in P), (\forall s \in S) \tag{28}$$

In objective function-1, the goal is to minimize the expected number of untreated casualties across all scenarios. The variable "Non" is computed within Constraints (10)–(15), considering the projected casualties at demand points and the casualties that have been assigned.

In objective function-2, the aim is to minimize the expected demand-weighted distance between disaster areas and EMCs. This function also accounts for road failures through distance increase ratios. In objective function-3, the goal is to minimize the expected number of additional doctors and nurses required in hospitals, as well as the number of doctors and nurses needed in TMCs. To calculate the variables "*De*", "*Ne*", "*Dt*" and "*Nt*." Constraints (19)–(22) take into consideration the existing number of doctors and nurses within hospitals, alongside the number of casualties assigned to EMCs.

Constraint (2) guarantees that the cumulative number of type-T1 and T2 casualties assigned to hospital-j from various demand points does not surpass the bed capacity of hospital-j during period-p of scenario-s. Similarly, Constraint (3) ensures that the total number of type-T2 casualties allocated to TMC-j from different demand points is below the bed capacity of TMC-j within the same period-p of scenario-s. Furthermore, Constraint (4) enforces that the total number of type-T3 casualties assigned to EMC-j from different demand points remains within the outpatient capacity of EMC-j during period-p of scenario-s. These constraints exhibit minor distinctions attributed to the problem definition: solely hospitals can accommodate type-T1 (immediate) casualties, and whereas type-T1 and T2 casualties use bed capacity ($k = 1$), type-T3 casualties use outpatient care capacity ($k = 2$) within EMCs.

Constraint (5) defines the initial capacities of EMCs before the disaster as the capacities in period-0. Subsequently, after the disaster unfolds (period-1), the available capacity of EMCs is adjusted in line with the damage ratio $\left(g_j^s\right)$ of EMCs, as detailed in Constraint (6). It is important to note that damage probability is pertinent only to hospitals, as TMCs are established post-disaster. Following the initial period, the available bed and outpatient capacities of EMCs are dynamically updated in Constraints (7)–(9). In these constraints, alongside the capacities and the casualties assigned in the preceding period, the transition probabilities of patients' health conditions are considered to recalibrate the EMC capacities. In this manner, Constraint (7) updates the bed capacity of hospitals, factoring in the death probabilities of immediate casualties and the healing probabilities of delayed casualties from the previous period. Similarly, Constraint (8) adjusts the bed capacity of TMCs, accounting for the healing probability of delayed patients and the previously assigned delayed patients. Finally, Constraint (9) updates the outpatient care capacity of EMCs, taking into account the healing and discharge probabilities of patients from the previous period.

The number of casualties assigned to EMCs is determined by considering the expected casualties in each disaster area and the total number of untreated casualties in that area from the previous period. Untreated casualties are attempted to be assigned to EMCs by carrying them over to the next period. For the first period, the number of expected casualties in each disaster area is equal to the total number of assigned and non-assigned casualties in that area. Constraints (10)–(12) refer to these equations for type-T1, T2 and T3 casualties, respectively. Additionally, the deterioration probability of the health condition of untreated casualties is considered in the subsequent periods while updating the capacity of the EMCs. To determine the demand for immediate casualties in the next periods, we consider two transition probabilities of health conditions: one for transitioning to a stable state and another for transitioning from delayed to immediate condition, as described in Constraint (13). Similarly, for delayed casualties, two health condition transition probabilities are considered: transitioning to a stable state and transitioning from a minimal state to a delayed state, as outlined in Constraint (14). Finally, the demand for minimal casualties is determined only by considering the stable states from the previous period, as presented in Constraint (15).

In Constraint (16), a distance limit is set for type-T1 (immediate) casualties to prevent their assignment to hospitals located at a substantial distance. Constraints (17) and (18) are formulated to ascertain the presence of assignments for type-T1 casualties from demand point-i to EMC-j in period-p of scenario-s. Accordingly, X_{ijT1}^{ps} will assume a value of 1 if an assignment exists and 0 otherwise. Thus, the distance limit applies exclusively to pertinent assignments.

Medical staff assignment constraints are outlined in Constraints (19)–(22). Constraint (19) determines the allocation of doctors from the coordination centre to each TMC based on the count of delayed casualties assigned to that TMC and the maximum number of delayed casualties that a doctor can attend to in a period. Constraint (20) calculates the required number of nurses in each TMC, accounting for the assigned delayed and minimal casualties. For hospitals with existing medical staff, the surplus doctors and nurses required are calculated. Constraint (21) determines the count of additional doctors needed in hospitals for immediate and delayed casualties, considering the current doctors within the hospitals. Similarly, Constraint (22) computes the supplementary nurses needed in hospitals for all assigned casualties, factoring in the existing nurses.

Constraint (23) establishes the reliable set, delineating the scenarios encompassed within the model. Constraints (24) and (25) stipulate that scenarios lacking untreated casualties across all periods are included in the reliable set. Finally, Constraints (26)–(28) govern binary, positive integer and positive variables, respectively.

3.3 Solution approach

The notion of an optimal solution in the realm of multi-objective modelling is referred to as Pareto optimal. A solution is considered Pareto optimal if there is no way to enhance any of its objective functions without concurrently undermining the performance of other objective functions. The ensemble of Pareto optimal solutions constitutes a set known as the Pareto set, as elucidated by Mavrotas (2009).

For solving multi-objective models, the ϵ-constraint method offers an efficient approach. Mavrotas (2009) introduced an enhanced rendition of this method called augmented ϵ-constraint method (AUGMECON), which addresses the limitations of the classical ϵ-constraint method. Furthermore, Mavrotas and Florios (2013) further refined this approach, called AUGMECON2, a particularly effective strategy for addressing multi-objective integer programming problems (Mavrotas and Florios, 2013). The notations used in the AUGMECON2 are as follows:

e_j: the parameters for the right-hand side for the specific iteration drawn from the grid points of the objective functions 2, 3,. . ., j.

r_j: the range of the respective objective functions 2, 3,. . ., j.

q_j: the length of the equal intervals of the objective functions 2, 3,. . ., j.

s_j: the surplus variables of the respective constraints and eps $\epsilon[10^{-6}, \quad 10^{-3}]$.

Suppose that we have an optimization problem with objectives-j ($j = 1,\ldots n$):

$$Max\ f_j(x)$$

s.t:

$$C(x) \leq 0; x \geq 0$$

The steps of AUGMECON2 are summarized below:

1 Solve the model for each objective-j separately.
2 Build the pay-off table according to the objective function results found in Step 1.
3 Find the minimum and maximum value of each (j–1) objective function, and call them f_{jmin} and f_{jmax}.
4 Find the range of each (j–1) objectives as follows: $r_j = f_{jmin} - f_{jmax}$.
5 Divide the range of each objective function into n equidistant grids, as long as $q_j = r_{j/}(n-1)$.
6 Define a slack variable s_j ($s_j \geq 0$) for each of the j^{th} objective functions to the model. Add a constraint for each (j–1) objectives as follows:

$$f_j(x) - s_j = e_j \tag{29}$$

7 Convert the objective function in the following form:

$$Max\ f_j(x) + eps\left(\frac{s_2}{r_2} + 0.1\frac{s_3}{r_3} + \ldots + 10^{-(j+2)}\frac{s_j}{r_j}\right) \tag{30}$$

8 Include the original constraints in the model. Hence, build the complete model.
9 At each iteration-i, compute $e_j = f_{jmin} + q_j i$ and change the right-hand side of the j^{th} constraint as e_j. Solve the model and save the results.
10 Complete n-iterations and complete the algorithm.

Because our model has multiple objectives, and AUGMECON2 is one of the most suitable algorithms for solving multi-objective problems, we used it to solve our problem. For a more detailed explanation of this algorithm, readers may refer to (Mavrotas and Florios, 2013).

4. Case study

To validate the proposed model, we conducted a real case study focusing on the Kartal district in Istanbul, an area projected to be significantly affected by a potential earthquake in Istanbul. Kartal, being the 11th most densely populated district in Istanbul, is home to approximately 470,000 residents. The district comprises 20 sub-districts, each serving as a demand point, and hosts 11 existing hospitals. In addition to the pre-existing hospital infrastructure, we identified 74 potential TMC locations. These candidate TMC locations encompass a range of spaces including schoolyards, mall parking lots and other suitable areas. The selection of these sites was guided by distinct criteria and involved leveraging tools such as Google Maps and the Kartal city guide website (Url–1), as visually represented in Figure 4.

We used casualty estimates derived from the "Possible Earthquake Loss Estimate Booklets" (IBB-KRDAE, 2020), a collaborative study between the Istanbul Metropolitan Municipality (IBB) and the Kandilli Observatory and Earthquake Research Institute (KRDAE). This comprehensive source provided projections for casualty figures across different sub-districts. Specifically, for a potential earthquake scenario of magnitude 7.5, we focused on Kartal's sub-districts. Table 2 offers a presentation of the expected casualty numbers corresponding to this specific earthquake scenario. These estimates, delineated by sub-districts, were distributed across periods in alignment with predefined rates. Specifically, the rates for the four periods were established as follows: 0.6, 0.25, 0.10 and 0.05. This signifies that 60% of the total expected casualties manifest in the first period, a distribution consistent with the approach taken by Rawls and Turnquist (2012).

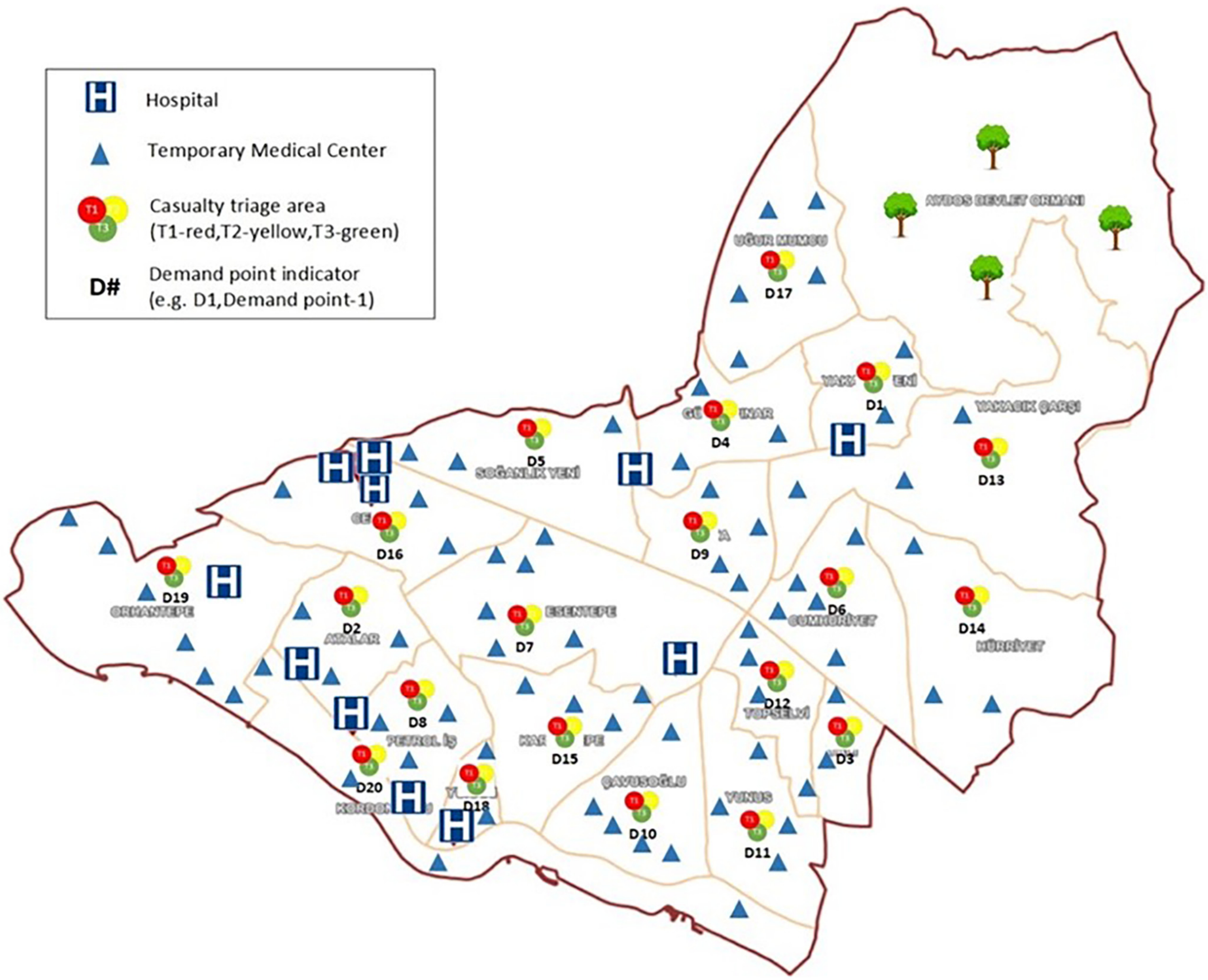
A collection of 20 scenarios was generated, encompassing the central scenario (S1) and progressively evolving towards more pessimistic projections as the scenario numbering ascends. Commencing from S2, it was hypothesized that the casualty count would increment by 10% compared to the preceding scenario. As a result, the most substantial estimate of anticipated casualties emerged in S20, effectively characterizing it as a pessimistic scenario. The occurrence probabilities of these scenarios were configured within the range of 0.01–0.1, reflecting their likelihood of transpiring.

The bed capacity and the current medical staff numbers in hospitals were sourced from the Statistical Report of Public Hospitals (2017). It was postulated that the outpatient care capacity of a hospital would be three times its bed capacity. Meanwhile, the bed and outpatient care capacities allocated to TMCs varied based on the location's suitability, falling within the ranges of 40–120 and 360–1,080, respectively. Furthermore, a working assumption was made that 60% of the medical staff available in hospitals would be accessible during the phase of post-disaster medical response.

The time taken for medical care provided by doctors and nurses for each casualty category (T1, T2 and T3) has been determined based on insights from experts in the field. Specifically, the service time for a doctor is projected to span between 30–120 min for an immediate (T1) casualty, 15–60 min for a delayed (T2) casualty and 5–15 min for a minimal casualty. Additionally, the service time of nurses has been set at half the duration of doctors' service time. Subsequently, a maximum threshold has been established for the number of casualties that a doctor and nurse can effectively attend to within a specified period for each scenario.

Various methodologies exist in the literature to address link or road failures in the event of a disaster. In our study, we have adopted the probabilistic approach to account for link failures, wherein we factor in the potential increase in distance due to road damage as indicated by the damage ratios of the roads for each scenario. Similarly, when dealing with disaster operations, it is common to consider the impact of partial or complete damage to facilities. In our analysis, we have considered the

Figure 4 The map of sub-districts (demand points), hospitals and candidate TMC locations in Kartal



Source: Figure adapted from Oksuz and Satoglu (2020)

possibility that hospitals may sustain partial damage following a disaster, resulting in adjustments to their capacities according to a designated capacity decrease ratio. We have chosen to distribute the damage ratios of roads uniformly within a range of 3%–38%, and for hospitals, the damage ratios are also uniformly distributed ranging from 0%–32%. These ranges have been determined based on a comprehensive report (JICA, 2002) jointly prepared by the IBB and the Japan Cooperation Agency.

To establish the transition probabilities governing the health condition changes of casualties, we developed two distinct transition matrices. These matrices are pivotal in defining the likelihood of health condition transitions for casualties, encompassing various triage categories. Our model includes not only the triage categories but also two supplementary categories: DC and D. For treated casualties, the transition probabilities that dictate their health condition shifts are outlined in Table 3. It captures the dynamics of health improvements and deteriorations for casualties under medical treatment. Conversely, Table 4 delineates the transition probabilities governing untreated casualties' health conditions. In this context, it is assumed that untreated casualties experience higher probabilities of health condition deterioration compared to their treated counterparts.

5. Computational results

The Pareto optimal (non-dominated) solutions generated by the proposed multi-objective model were obtained using the CPLEX 12.6 solver on a personal computer with an i7-4510U CPU 2.0 GHz for the real case study. In this analysis, a distance limit of 7 km was applied for immediate (T1) casualties, and an α-reliability level of 0.9 was selected. The model was initially solved for each of the three objective functions independently, resulting in a pay-off table as depicted in Table 5. The computational times required for solving each objective function were 54 s, 17.1 min and 83 s, respectively.

As illustrated in Table 5, the minimization of the expected number of untreated casualties (obj-1) yields an outcome of 24,158.83 for the expected total demand-weighted distance

Table 2 Estimated number of casualties based on an earthquake scenario

Sub-districts	Dead	Immediate (T1)	Delayed (T2)	Minimal (T3)
Atalar	12	5	33	68
Cevizli	9	5	27	57
Cumhuriyet	2	0	12	28
Cavusoglu	7	3	20	40
Esentepe	5	2	21	48
Gumuspinar	7	3	22	49
Hurriyet	13	7	48	107
Karlıktepe	11	6	33	68
Kordonboyu	10	5	29	55
Orhantepe	18	8	57	114
Orta	3	1	10	23
Petrol Is	11	5	31	63
Soganlik Yeni	6	2	20	45
Topselvi	8	4	22	44
Ugur Mumcu	16	8	47	91
Yakacik Carsi	5	3	21	48
Yakacik Yeni	7	4	24	50
Yali	11	7	29	56
Yukari	6	3	16	31
Yunus	9	6	31	63
Total	*176*	*87*	*553*	*1,148*

Source: Table created by authors; IBB-KRDAE (2020)

Table 3 The Markov chain matrix indicating the transition probabilities of the health condition of treated casualties

States	D	T1	T2	T3	DC
D	1				
T1	0.15	0.6	0.25		
T2		0.1	0.2	0.7	
T3			0.05	0.15	0.8
DC					1

Source: Table created by authors

Table 4 The Markov Chain matrix indicating the transition probabilities of the health condition of untreated casualties

States	D	T1	T2	T3
D	1			
T1	0.6	0.4		
T2		0.55	0.45	
T3			0.25	0.75

Source: Table created by authors

Table 5 Pay-off table

Objectives	Z1 (untreated)	Z2 (distance)	Z3 (med.staff)
Min Z1 (untreated)	*0*	24,158.83	66
Min Z2 (distance)	2,839	*5,456.76*	79.48
Min Z3 (med.staff)	420	23,840.53	*1.07*

Source: Table created by authors

between demand points and EMCs (obj-2), with a corresponding expected number of medical staff needed for EMCs (obj-3) amounting to 66. In contrast, prioritizing the minimization of obj-2 results in obj-1 reaching 2839, whereas obj-3 becomes 79.48. Finally, if the focus shifts to minimizing obj-3, obj-1 will be reduced to 420, whereas obj-2 will have a value of 23,840.53.

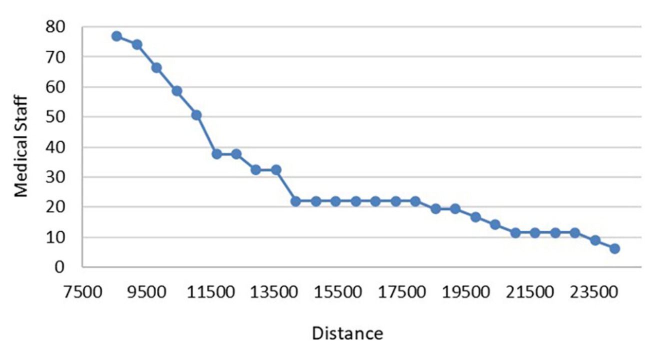
From the pay-off table, we calculated the ranges of the second and third objective functions as $r2 = 18702.07$ and $r3 = 78.41$, respectively. Then, we divide the two ranges into 30 equal intervals (q) with $step2 = 623.4$ and $step3 = 2.61$. The AUGMECON2 process for all grid points is as follows:

For $i = 0$ to 30
$e3 = 1.07 + i \times 2.61$
For $j = 0$ to 30
$e2 = 5456.76 + j \times 623.4$
Solve model
Next j
Next i

Pareto optimal solutions were successfully identified by encompassing the permissible ranges for obj-2 and obj-3. Through this approach, we achieved Pareto optimal solutions across 26 out of 30 grid points, as detailed in Table A1. Unfortunately, the model could not converge to a solution for the initial four experiments (e1 to e4) within the allocated 7,200-s time frame. The average CPU time for the 26 Pareto optimal solutions amounted to 158 s. The α-reliability level was set to 0.9 for this case study. Upon examining Table A1, it is evident that the expected total number of untreated casualties (Z1) for all Pareto optimal solutions is zero. This outcome signifies the realization of the α-reliability level at a full 100%, as all expected casualties were effectively allocated to EMCs. To facilitate a comprehensive understanding, Figure 5 presents a comparative assessment of the objective values for Z2 and Z3.

A noticeable trend emerges, where an increase in the total expected distance correlates with a decrease in the expected number of required medical staff. This outcome can be attributed to the model's strategy of assigning casualties across extended distances, thus contributing to a reduction in the necessary medical staff. This approach arises from the fact that hospitals, which already possess medical staff, are being used, even if the distance between demand points and hospitals is substantial.

Figure 5 The comparison of obj-2 (distance) and obj-3 (medical staff)



Source: Figure created by authors

Upon evaluation of the Pareto optimal solutions, Experiment-5 emerged as the most effective solution. This selection is rooted in the fact that we grant higher priority to minimizing the distance/response time (obj-2) compared to the requirement for medical staff (obj-3). Consequently, the outcomes presented pertain to the solution derived from Experiment-5, characterized by the lowest obj-2 value. Figure 6 illustrates the expected number of necessary TMCs, doctors and nurses for each scenario under Experiment-5. Notably, the number of TMCs generally increases as scenarios transition from optimistic (S1) to pessimistic (S20). This trend emerges because the model strives to allocate all casualties to medical centres with a 0.9 α-reliability level, thereby minimizing untreated casualties. Consequently, additional TMCs are opened to facilitate this objective. In tandem, as the number of anticipated casualties escalates across scenarios, the requisite medical staff also witnesses a proportional rise. Moreover, the model accords priority to existing hospitals, thereby curbing the need for deploying additional medical staff to medical centres.

Figure 7 illustrates the outcomes concerning the number of casualties assigned to EMCs corresponding to each demand point, focusing on the worst-case scenario (S20) within Experiment-5. Given that all expected casualties were feasibly assigned to EMCs for this case study, the figure effectively delineates the demand for each disaster area (sub-district). As evidenced, D14, D17 and D19 sub-districts exhibit a higher expected number of casualties in contrast to others. While D14 and D17 boast larger populations, D19's population is smaller than certain sub-districts such as D2 and D15. This divergence might be attributed to factors underlying the study conducted by IBB-KRDAE (2020), which deemed disaster area D19 as posing a higher risk.

In this study, a holistic perspective is presented in contrast to the previous studies, as the TMCs to be located and the number of medical personnel to be allocated are planned simultaneously for disaster response. Hence, realistic and applicable results have been obtained. In addition, treatment and deterioration of the casualties' health status were modelled as Markov Chains, and these transitions were included in the proposed stochastic programming model constraints, which is another unique aspect of our study.

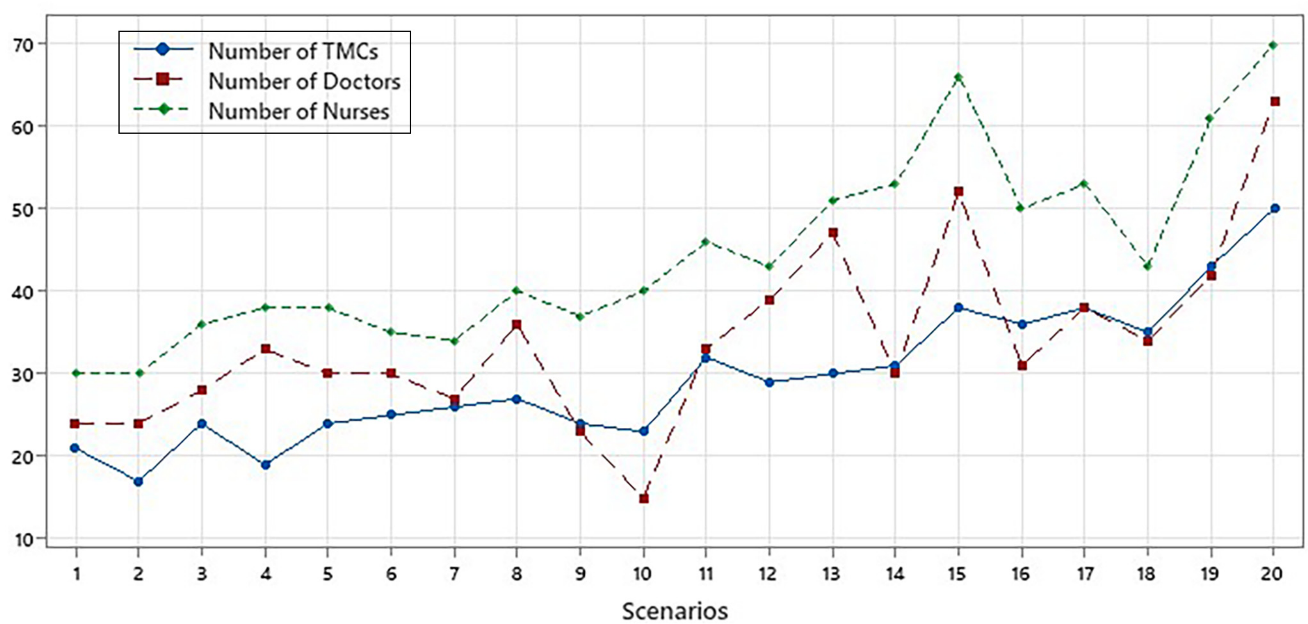
6. The managerial and theoretical implications

The significant contributions of this study to the fields of disaster management and HT that offer valuable insights for both practical and academic endeavours are explained below:

Managerial implications:

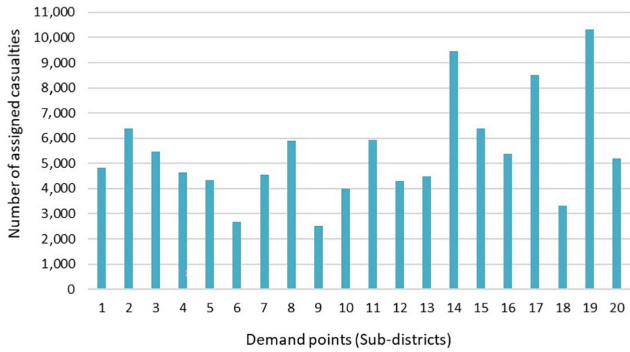
- *Resource allocation*: This study highlights the critical importance of efficient resource allocation, including the strategic positioning of TMCs and the allocation of medical staff. This has practical implications for disaster management agencies and health care organizations in optimizing their response capabilities.
- *Multi-period planning*: The adoption of multi-period planning models, as proposed in this study, can improve the responsiveness of EMS over time. This approach enables better resource utilization and the ability to adapt to the changing dynamics of disaster-affected regions.
- *Dynamic capacity updates*: The consideration of dynamic capacity updates based on assigned casualties in each period is a novel approach. This can guide disaster response decision-makers in effectively managing and

Figure 6 The expected number of TMCs, doctors and nurses needed for each scenario



Source: Figure created by the authors

Figure 7 The number of assigned casualties to the EMCs according to each demand point



Source: Figure created by authors

expanding medical centre capabilities during ongoing disaster situations.

Theoretical implications:

- *Multi-objective model*: This study introduces a novel multi-objective dynamic stochastic optimization model, addressing the combined aspects of multi-period TMC location planning, casualty allocation and medical staff planning within an uncertain context. This model contributes to the theoretical foundation of disaster management.
- *α-Reliability levels*: The application of α-reliability levels (chance constraints) is a theoretical innovation in addressing disaster response challenges. This approach can inspire further research into more robust and reliable models for disaster planning.
- *Discrete-time Markov Chain*: The incorporation of a discrete-time Markov Chain approach to reflect the stochastic nature of casualties' health conditions adds to the theoretical sophistication of the model. This approach has the potential for broader application in related fields.
- *Realistic capacity division*: The division of medical centre capacities into bed and outpatient care capacity, along with considering possibilities for road and hospital damage, contributes to more realistic theoretical models for disaster response.
- *Distance limit constraints*: The use of distance limit constraints ensures that immediate casualties are not assigned to hospitals located far away, and this is a valuable contribution to the theoretical framework of disaster response optimization.

7. Conclusion

In this study, a post-disaster emergency medical response system has been considered, including the location planning of medical centres, the allocation of casualties and medical staff assignment. A multi-objective dynamic stochastic model was used in emergency response such as the health condition of casualties, possibilities of damage to roads and estimated hospitals and α-reliability levels for untreated casualties. To the best of our knowledge, there is no past study that considers multi-period planning of the TMCs locations, assignment of casualties and medical staff planning simultaneously under uncertainty, for disaster response. Besides, we aimed multiple objectives and embedded the patients' health status transition probabilities into our model with Markov Chains. These are the unique aspects of our study.

The subjects investigated within this study encompass vital and top-priority planning considerations, aligning with the tenets outlined in Turkey's Disaster Response Plan and the National Earthquake Strategy and Action Plan. As these reports are authored by the Disaster and Emergency Management Presidency (AFAD), the designated body responsible for disaster coordination and planning, the findings of this study hold the potential to furnish managerial perspectives for AFAD's operations. Furthermore, the addressed issues bear relevance to the city and regional planning department and local municipalities, particularly in terms of formulating strategies for TMC placements.

The study does entail certain academic and managerial constraints about the addressed issues. A foremost limitation revolves around the task of pinpointing the optimal locations for the potential TMCs ahead of a disaster occurrence. This decision carries strategic significance and mandates adherence to official plans. Ideally, collaboration with local institutions should guide the selection of candidate sites, enabling alignment with the evolving urban landscape. Such a proactive approach is essential, given the risk of candidate locations losing suitability over time because of urban development activities. Consequently, periodic assessments are imperative to ensure the ongoing viability of the chosen sites. Another notable limitation pertains to the collection of data for envisaged disaster scenarios. This step is pivotal and demands a realistic approach anchored in official reports and relevant studies. The accurate compilation and generation of data bear equal weight to the precise modelling of the problem itself. Thoroughly vetted and accurate data serves as the foundation for robust analysis and sound decision-making, amplifying the importance of this data collection process.

A pivotal aspect within the post-disaster medical response system involves the accurate coordination of medical staff, considering the inherent uncertainty surrounding casualty numbers within the affected regions. The allocation of casualties to EMCs and the associated need for medical resources are elaborately linked. To ensure a swift and efficient medical response, it is imperative to holistically plan the resource allocation across EMCs. In addressing this challenge, the AUGMECON2 method, as introduced by Mavrotas and Florios (2013), proved instrumental in tackling the multi-objective model proposed for the case study. The findings were comprehensively evaluated, and emphasis was placed on the most impactful Pareto optimal solution. The outcome indicated that both the existing hospitals and recommended TMCs are equipped to accommodate the anticipated volume of casualties following a potential earthquake in Kartal across all scenarios. However, the number of TMCs necessitated post-earthquake deployment exhibited variations based on the respective scenarios. Instances of heightened expected casualty figures corresponded to an increased demand for TMCs. For instance, the worst-case scenario required the establishment of 50 TMCs, whereas the base scenario necessitated 21. Further insights were derived, determining the requisite medical staff complement for each EMC. This insight informed the determination of surplus doctors and nurses needed in hospitals, as well as the corresponding medical staff allocation for TMCs. The solution time associated with the proposed model remained acceptable within the context of the case study. Nevertheless, for larger-scale scenarios, the potential exists for escalated computation times. In such scenarios, the application of meta-heuristic algorithms can be a valuable strategy to expedite solution times. Additionally, the implementation of techniques such as Bender's decomposition or effective cutting plane methodologies can effectively address problems while maintaining a manageable computational overhead.

This study relies on some assumptions and data sources, including casualty estimates. Inaccuracies in these assumptions can impact the validity of the model's results. The proposed models may require real-time data and information exchange for optimal decision-making, which can be challenging to implement in disaster-affected areas with disrupted communication. The study primarily focuses on logistical and resource allocation aspects and does not account for external factors such as political, economic and regulatory considerations, which can significantly impact disaster management strategies. In future studies, a more nuanced classification of casualties could yield valuable insights, particularly by incorporating factors such as the nature of injuries or specific medical requirements. This classification can inform the allocation of casualties to EMCs based on their specialized capabilities. Hospitals, for instance, exhibit varying capacities for critical facilities such as operating rooms, dialyzers and respirators. Moreover, a detailed consideration of TMCs' equipment profiles is essential. While certain TMCs may possess specialized equipment, especially those situated in expansive venues like sports halls, a standardized equipment assessment might not hold for all. An often-overlooked aspect of EMS research pertains to deceased patients. Therefore, broadening the scope of casualty types, encompassing immediate, minimal and deceased patients, stands as a crucial avenue for exploration. Additionally, the influence of secondary disasters, such as tsunamis and aftershocks following the primary event, is an area ripe for investigation. Such subsequent events can severely impact emergency response efforts, necessitating specialized strategies for effective management. By comprehensively addressing these aspects, future studies can provide an enriched understanding of post-disaster medical response, equipping disaster management authorities with well-rounded insights to handle complex scenarios.

References

Adarang, H., Bozorgi-Amiri, A., Khalili-Damghani, K. and Tavakkoli-Moghaddam, R. (2020), "A robust bi-objective location-routing model for providing emergency medical services", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 10 No. 3, pp. 285-319.

Ahadian, S., Pishvaee, M.S. and Jahani, H. (2023), "Reorganization of a medical service network to manage pandemic waves: a real case study", *Operations Research for Health Care*, Vol. 39, p. 100410.

Ahmadi-Javid, A., Seyedi, P. and Syam, S.S. (2017), "A survey of healthcare facility location", *Computers & Operations Research*, Vol. 79, pp. 223-263.

Alizadeh, M., Amiri-Aref, M., Mustafee, N. and Matilal, S. (2019), "A robust stochastic casualty collection points location problem", *European Journal of Operational Research*, Vol. 279 No. 3, pp. 965-983.

Altay, N. and Green, W.G. III (2006), "Or/MS research in disaster operations management", *European Journal of Operational Research*, Vol. 175 No. 1, pp. 475-493.

Aydin, N. (2016), "A stochastic mathematical model to locate field hospitals under disruption uncertainty for large-scale disaster preparedness", *An International Journal of Optimization and Control: Theories & Applications (IJOCTA)*, Vol. 6 No. 2, pp. 85-102.

Babaqi, T. and Vizvari, B. (2023), "The post-disaster transportation of injured people when hospitals have districts", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 13 No. 1, pp. 61-73.

Barbarosoğlu, G., Özdamar, L. and Çevik, A. (2002), "An interactive approach for hierarchical analysis of helicopter logistics in disaster relief operations", *European Journal of Operational Research*, Vol. 140 No. 1, pp. 118-133.

Caglayan, N. and Satoglu, S.I. (2021), "The multi-objective two-stage stochastic programming model for a proposed casualty transportation system in large-scale disasters: a case study", *Mathematics*, Vol. 9 No. 4, p. 316.

Caunhye, A.M. and Nie, X. (2018), "A stochastic programming model for casualty response planning during catastrophic health events", *Transportation Science*, Vol. 52 No. 2, pp. 437-453.

Chang, K.H., Chen, T.L., Yang, F.H. and Chang, T.Y. (2023), "Simulation optimization for stochastic casualty collection point location and resource allocation problem in a mass casualty incident", *European Journal of Operational Research*, Vol. 309 No. 3, pp. 1237-1262.

Erbeyoğlu, G. and Bilge, Ü. (2020), "A robust disaster preparedness model for effective and fair disaster response", *European Journal of Operational Research*, Vol. 280 No. 2, pp. 479-494.

Farahani, R.Z., Lotfi, M.M., Baghaian, A., Ruiz, R. and Rezapour, S. (2020), "Mass casualty management in disaster scene: a systematic review of OR&MS research in humanitarian operations", *European Journal of Operational Research*, Vol. 287 No. 3, pp. 787-819.

Feng, C.M. and Wang, T.C. (2003), "Highway emergency rehabilitation scheduling in post-earthquake 72 hours", *Journal of the 5th Eastern Asia Society for Transportation Studies*, Vol. 5, pp. 3276- 3285.

Fereiduni, M. and Shahanaghi, K. (2017), "A robust optimization model for distribution and evacuation in the disaster response phase", *Journal of Industrial Engineering International*, Vol. 13 No. 1, pp. 117-141.

Ghasemi, P., Goodarzian, F. and Abraham, A. (2022), "A new humanitarian relief logistic network for multi-objective optimization under stochastic programming", *Applied Intelligence*, Vol. 52 No. 12, pp. 13729-13762.

Ghasemi, P., Khalili-Damghani, K., Hafezalkotob, A. and Raissi, S. (2020), "Stochastic optimization model for distribution and evacuation planning (a case study of Tehran earthquake)", *Socio-Economic Planning Sciences*, Vol. 71, p. 100745.

Gu, J., Zhou, Y., Das, A., Moon, I. and Lee, G.M. (2018), "Medical relief shelter location problem with patient severity under a limited relief budget", *Computers & Industrial Engineering*, Vol. 125, pp. 720-728.

Gupta, S., Starr, M.K., Farahani, R.Z. and Matinrad, N. (2016), "Disaster management from a POM perspective: mapping a new domain", *Production and Operations Management*, Vol. 25 No. 10, pp. 1611-1637.

Holguín-Veras, J., Pérez, N., Jaller, M., Van Wassenhove, L.N. and Aros-Vera, F. (2013), "On the appropriate objective function for post-disaster humanitarian logistics models", *Journal of Operations Management*, Vol. 31 No. 5, pp. 262-280.

Horner, M.W. and Widener, M.J. (2011), "The effects of transportation network failure on people's accessibility to hurricane disaster relief goods: a modeling approach and application to a Florida case study", *Natural Hazards*, Vol. 59 No. 3, pp. 1619-1634.

Huang, R., Kim, S. and Menezes, M.B. (2010), "Facility location for large-scale emergencies", *Annals of Operations Research*, Vol. 181 No. 1, pp. 271-286.

IBB-KRDAE (2020), "Possible earthquake loss estimate booklets", available at: https://depremzemin.ibb.istanbul/guncelcalismalarimiz/

Jia, H., Ordóñez, F. and Dessouky, M. (2007), "A modeling framework for facility location of medical services for large-scale emergencies", *IIE Transactions*, Vol. 39 No. 1, pp. 41-55.

JICA (2002), The Study on a Disaster Prevention/Mitigation Basic Plan in Istanbul including Seismic Microzonation in the Republic of Turkey, Japan International Cooperation Agency, Final Report, Vol. 5.

Kohn, S., Eaton, J.L., Feroz, S., Bainbridge, A.A., Hoolachan, J. and Barnett, D.J. (2012), "Personal disaster preparedness: an integrative review of the literature", *Disaster Medicine and Public Health Preparedness*, Vol. 6 No. 3, pp. 217-231.

Liu, Y., Cui, N. and 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*, Vol. 128, pp. 1-16.

Liu, J., Li, Y., Li, Y., Zibo, C., Lian, X. and Zhang, Y. (2023), "Location optimization of emergency medical facilities for public health emergencies in megacities based on genetic algorithm", *Engineering, Construction and Architectural Management*, Vol. 30 No. 8, pp. 3330-3356.

Lodree, E.J., Altay, N. and Cook, R.A. (2019), "Staff assignment policies for a mass casualty event queuing network", *Annals of Operations Research*, Vol. 283 Nos 1/2, pp. 411-442.

Lu, Q., Goh, M. and De Souza, R. (2013), "Learning mechanisms for humanitarian logistics", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 3 No. 2, pp. 149-160.

Mavrotas, G. (2009), "Effective implementation of the ε-constraint method in multi-objective mathematical programming problems", *Applied Mathematics and Computation*, Vol. 213 No. 2, pp. 455-465.

Mavrotas, G. and Florios, K. (2013), "An improved version of the augmented ε-constraint method (AUGMECON2) for finding the exact Pareto set in multi-objective integer programming problems", *Applied Mathematics and Computation*, Vol. 219 No. 18, pp. 9652-9669.

Mills, A.F., Argon, N.T. and Ziya, S. (2018), "Dynamic distribution of patients to medical facilities in the aftermath of a disaster", *Operations Research*, Vol. 66 No. 3, pp. 716-732.

Nandi, S. (2022), "Disaster risk management during COVID-19 pandemic", *COVID-19 and the Sustainable Development Goals*, Elsevier, pp. 325-348.

Niessner, H., Rauner, M.S. and Gutjahr, W.J. (2018), "A dynamic simulation–optimization approach for managing mass casualty incidents", *Operations Research for Health Care*, Vol. 17, pp. 82-100.

Oksuz, M.K. and 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*, Vol. 44, p. 101426.

Özdamar, L. and Demir, O. (2012), "A hierarchical clustering and routing procedure for large scale disaster relief logistics planning", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 48 No. 3, pp. 591-602.

Pouraliakbarimamaghani, M., Mohammadi, M. and Mirzazadeh, A. (2018), "A multi-objective location-allocation model in mass casualty events response", *Journal of Modelling in Management*, Vol. 13 No. 1, pp. 236-274.

Puterman, M.L. (2014), *Markov Decision Processes: discrete Stochastic Dynamic Programming*, John Wiley & Sons, Hoboken, New Jersey.

Rath, S., Gendreau, M. and Gutjahr, W.J. (2016), "Bi-objective stochastic programming models for determining depot locations in disaster relief operations", *International Transactions in Operational Research*, Vol. 23 No. 6, pp. 997-1023.

Rawls, C.G. and Turnquist, M.A. (2012), "Pre-positioning and dynamic delivery planning for short-term response following a natural disaster", *Socio-Economic Planning Sciences*, Vol. 46 No. 1, pp. 46-54.

Repoussis, P.P., Paraskevopoulos, D.C., Vazacopoulos, A. and Hupert, N. (2016), "Optimizing emergency preparedness and resource utilization in mass-casualty incidents", *European Journal of Operational Research*, Vol. 255 No. 2, pp. 531-544.

Russell, L.A., Goltz, J.D. and Bourque, L.B. (1995), "Preparedness and hazard mitigation actions before and after two earthquakes", *Environment and Behavior*, Vol. 27 No. 6, pp. 744-770.

Safeer, M., Anbuudayasankar, S.P., Balkumar, K. and Ganesh, K. (2014), "Analyzing transportation and distribution in emergency humanitarian logistics", *Procedia Engineering*, Vol. 97, pp. 2248-2258.

Salman, F.S. and Gül, S. (2014), "Deployment of field hospitals in mass casualty incidents", *Computers & Industrial Engineering*, Vol. 74, pp. 37-51.

Salmerón, J. and Apte, A. (2010), "Stochastic optimization for natural disaster asset pre-positioning", *Production and Operations Management*, Vol. 19 No. 5, pp. 561-574.

Saoud, N.B.B., Mena, T.B., Dugdale, J., Pavard, B. and Ahmed, M.B. (2006), "Assessing large scale emergency rescue plans: an agent based approach", *The International Journal of Intelligent Control and Systems*, Vol. 11 No. 4, pp. 260-271.

Shahriari, M., Bozorgi-Amiri, A., Tavakoli, S. and Yousefi-Babadi, A. (2017), "Bi-objective approach for placing ground and air ambulance base and helipad locations in order to optimize EMS response", *The American Journal of Emergency Medicine*, Vol. 35 No. 12, pp. 1873-1881.

Shavarani, S.M., Golabi, M. and Vizvari, B. (2019), "Assignment of medical staff to operating rooms in disaster preparedness: a novel stochastic approach", *IEEE Transactions on Engineering Management*, Vol. 67 No. 3, pp. 593-602.

Statistical Report of Public Hospitals (2017), "General directorate of public hospitals and TR ministry of health", available at: https://khgm.saglik.gov.tr/TR,40113/kamu-hastaneleri-istatistik-raporu–2017.html (accessed 19 August 2018).

Sun, H., Wang, Y. and Xue, Y. (2021), "A bi-objective robust optimization model for disaster response planning under uncertainties", *Computers & Industrial Engineering*, Vol. 155, p. 107213.

Toro-DíAz, H., Mayorga, M.E., Chanta, S. and Mclay, L.A. (2013), "Joint location and dispatching decisions for emergency medical services", *Computers & Industrial Engineering*, Vol. 64 No. 4, pp. 917-928.

Turkeš, R., Cuervo, D.P. and Sörensen, K. (2019), "Pre-positioning of emergency supplies: does putting a price on human life help to save lives?", *Ann Oper Res*, Vol. 283, pp. 865-895, doi: 10.1007/s10479-017-2702-1.

Turkeš, R., Sörensen, K. and Cuervo, D.P. (2023), "Design of experiments in humanitarian logistics: facility decision making in disaster preparedness", *International Transactions in Operational Research*, Vol. 30 No. 6, pp. 4078-4106.

Van Wassenhove, L.N. and Pedraza Martinez, A.J. (2012), "Using or to adapt supply chain management best practices to humanitarian logistics", *International Transactions in Operational Research*, Vol. 19 Nos 1/2, pp. 307-322.

Wilson, D.T., Hawe, G.I., Coates, G. and Crouch, R.S. (2013), "A multi-objective combinatorial model of casualty processing in major incident response", *European Journal of Operational Research*, Vol. 230 No. 3, pp. 643-655.

Xiang, B., Cheng, W., Liu, J., Huang, L., Li, Y. and Liu, L. (2009), "Triage of pediatric injuries after the 2008 Wen-Chuan earthquake in China", *Journal of Pediatric Surgery*, Vol. 44 No. 12, pp. 2273-2277.

Yaesoubi, R. and Cohen, T. (2011), "Generalized Markov models of infectious disease spread: a novel framework for developing dynamic health policies", *European Journal of Operational Research*, Vol. 215 No. 3, pp. 679-687.

Yi, W. and Kumar, A. (2007), "Ant colony optimization for disaster relief operations", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 43 No. 6, pp. 660-672.

Yi, W. and Özdamar, L. (2007), "A dynamic logistics coordination model for evacuation and support in disaster response activities", *European Journal of Operational Research*, Vol. 179 No. 3, pp. 1177-1193.

Further reading

Url-1 (2023), Kartal city guide, available at: https://belnet.kartal.bel.tr/keos/ (accessed 17 March 2023).

Appendix

Table A1 Pareto optimal solution results

Experiment	Z1	Z2	Z3
1	NA	6,080	98
2	NA	6,703	95
3	NA	7,327	92
4	NA	7,950	82
5	*0*	*8,574*	*77*
6	0	9,197	74
7	0	9,821	66
8	0	10,444	59
9	0	11,067	51
10	0	11,691	38
11	0	12,314	38
12	0	12,938	32
13	0	13,561	32
14	0	14,184	22
15	0	14,808	22
16	0	15,431	22
17	0	16,055	22
18	0	16,678	22
19	0	17,301	22
20	0	17,925	22
21	0	18,548	19
22	0	19,172	19
23	0	19,795	17
24	0	20,418	14
25	0	21,042	12
26	0	21,665	12
27	0	22,289	12
28	0	22,912	12
29	0	23,535	9
30	0	24,159	6

Source: Table created by author

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