Annals of Operations Research (2022) 319:211–257
https://doi.org/10.1007/s10479-021-04003-5

S.I. : DESIGN AND MANAGEMENT OF HUMANITARIAN SUPPLY CHAINS

An integrative location-allocation model for humanitarian logistics with distributive injustice and dissatisfaction under uncertainty

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Accepted: 19 February 2021 / Published online: 31 March 2021

Abstract
Humanitarian logistics is an integral part of disaster relief operations, which involves the phases of preparedness, disaster operations, and post-disaster operations. Integrating the planning and execution between phases minimizes the gaps in providing relief to the affected population. This paper presents a two-stage multi-objective mathematical model for integrated decision-making during the preparation and response phases. The proposed model is developed to jointly optimize the location of emergency shelters (and/or depots) and coordinate the movement of relief vehicles between the disaster site and emergency shelters. Focusing on the optimal distribution of relief supplies to the emergency shelters, the proposed model aims to minimize the operational, distributive injustice, and dissatisfaction costs. To address the computational complexity of the introduced model, two multi-objective meta-heuristics, namely multi-objective vibration damping optimization and non-dominated sorting genetic algorithm (NSGA-II), are used. A comprehensive sensitivity analysis is conducted to study the impacts of variations in key parameters on model output under different scenarios. Our results suggests that the employed solution algorithms outperform the traditional optimization methods in achieving the Pareto-Front solutions.

Keywords Humanitarian relief logistics · Integrated emergency evacuation planning · Location-allocation · Robust optimization · Multi-objective meta-heuristics · Distributive injustice

1 Introduction

Natural and manmade disasters affect millions of people every year and leave behind a trail of devastation, impacting human life, possessions, and communities. Humanitarian logistics is the process of evacuating people from the disaster sites to safer areas to reduce the post-disaster causalities. It also ensures that relief services and supplies are provided to

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shelters in adequate quantities and on time (Li et al., 2012). The frequent occurrence of natural and manmade disasters in recent years has raised the need to develop novel models that can accelerate emergency aids to the communities affected by disasters and minimize post-disaster casualties (Dubey et al., 2019a; b; Gunasekaran et al., 2018).

Prior studies on disaster relief operations can be broadly classified into disaster preparedness and disaster response (Sheu, 2007). Several studies focus on effective disaster preparedness by identifying the potential disaster risks and their impacts to effectively plan the resources for relief planning (Campbell & Jones, 2011; Cavdur et al., 2016). On the other hand, some studies focused on the identification of evacuation sites to move the affected people into the nearest safe zones in case of disaster occurrence. In this direction, Kilci et al. (2015) have developed a mathematical model that simultaneously locates evacuation sites and optimizes the utilization of these sites during an earthquake. Similar work is reported by Zahiri et al. (2017) and Raziei et al. (2018). Another crucial decision in disaster preparedness is ensuring enough stock of relief supplies to provide an immediate response to the victims (Kovács & Spens, 2009). Because of this, several researchers have developed various location-allocation models for locating the distribution centers and the level of inventory to be stocked at each center (Ni et al., 2018; Yang et al., 2016). However, these studies overlooked the importance of demand uncertainty which is an inherent characteristic of the disaster relief inventory planning problem. To address this issue, Falasca and Zobel (2011) have proposed a two-stage model for the procurement in a disaster scenario considering demand uncertainty. Davis et al. (2013) have developed a stochastic model for prepositioning and distribution of relief supplies considering traffic congestion and time constraints.

Apart from disaster preparedness, there is also an increased effort from the researchers to propose reactive models for effective disaster response. Immediately after the disaster, there is an urgent need to evacuate people from disaster sites and shift them to safer locations. In this direction, several researchers made significant contributions (Najafi et al., 2013; Bish et al., 2014; Bayram et al., 2015; Jin et al., 2015; Pyakurel et al., 2019). The role of inventory planning and prepositioning and optimization of the stock of relief supplies is also highlighted in the literature (Whybark, 2007). Another important aspect of disaster relief is an immediate distribution of relief supplies to the rescued population.

It is often observed that multiple agencies are involved at various stages of a humanitarian supply chain to deal with significant challenges of disaster relief operations. However, the overall effectiveness of humanitarian logistics activities can be hampered by the lack of coordination between several stages and actors of decentralized humanitarian supply chains (Balcik et al., 2010; Dubey et al., 2019a; b; Özdamar et al., 2004). The disconnect between disaster planning and various levels of disaster response stages can be addressed through the integrated planning of these activities and increased coordination between various actors. It is observed that although there is a significant increase in research in the field of humanitarian logistics, most of the papers focus on very specific problems, such as shelter location identification, optimizing the warehouses, inventory planning, distribution network planning (Tofighi et al., 2016; Toyasaki et al., 2017; Rodríguez-Espíndola et al., 2018; Sabouhi et al. 2019). This limits the applicability and utility of these models in a real disaster scenario, in which most decisions are dependent on decisions made in other stages and by different agencies. Therefore, there is an urgent need to focus on developing integrated models for humanitarian logistics. However, due to the large number of variables involved and uncertainty in some parameters, the computational complexity of such integrated problems can be very high. So, there is also a need to propose effective solution methodologies that enable the decision-makers to solve such computationally complex problems in real time.

To address the above concerns, this paper aims to answer the following research questions (RQ):

RQ1 How to locate emergency shelters and depots jointly during a pre-disaster stage?
RQ2 How to optimally plan the routes and vehicles for the evacuation of people during disaster response when demand is uncertain?
RQ3 How to optimally plan the distribution of relief supplies to the evacuated people in a coordinated manner and in a reasonable time with the lowest level of social injustice and dissatisfaction during the disaster response?

To answer the above research questions, this paper proposes an integrated two-stage mathematical model to coordinate the relief efforts by jointly optimizing the emergency shelter location, depot location, evacuation route planning, and distribution of relief supplies to the evacuated people. The proposed model integrates disaster preparedness through the identification of optimal facility locations for emergency shelters as well as for depots required for prepositioning of relief supplies. Based on the information from a disaster preparedness stage, the model optimizes the evacuation as well as distribution decisions in a disaster response stage. In the disaster response stage, the model optimizes the route plan for the vehicles in the evacuation of victims from the disaster site to the emergency shelters. The model also simultaneously optimizes the route plan for the vehicle during the distribution of relief supplies from depots to the rescued people in the emergency shelters to minimize the lead time to prevent the feeling of distributive injustice among the rescued people.

Incorporating demand uncertainty as an influential factor and using a robust optimization method, the proposed model is solved for a real-case study of the city of Tehran. To address the computational complexity of the proposed model, two widely used meta-heuristics, namely NSGA-II and MOVDO are employed. Extensive computational experiments are carried to examine the impacts of varying the key parameters under different scenarios. The findings of the study suggest that the proposed solution algorithms outperform the traditional optimization methods in achieving Pareto-Front solutions. This paper contributes to the body of knowledge by proposing an integrated model jointly optimizing the decisions at various stages of humanitarian logistics, which can lead to better coordination among various actors and the overall effectiveness of disaster relief activities.

The remainder of this paper is structured as follows: In Sect. 2, the literature review, research gaps, and research objectives are presented. The proposed model is discussed in Sect. 3. Section 4 presents the developed solution methods. Section 5 discusses the case study. The computational experiments are presented in Sects. 6 and 7 provides managerial insights and discussion. Finally, the concluding remarks and future works are provided in Sect. 8.

2 Literature review

Our literature survey on humanitarian logistics is categorized into four subsections. Section 2.1 reviews the literature on disaster preparedness. Section 2.2 reviews the literature on disaster response. Section 2.3 reviews the literature on integration models or coordination in humanitarian logistics. Section 2.4 reviews the literature on solution methods employed in solving humanitarian logistics problems. Finally, the gaps identified from the literature and research objectives of this study are presented in Sect. 2.5.

2.1 Review on disaster preparedness

Disaster preparedness has gained significant attention from both academicians and practitioners over the last two decades. The importance of strategic planning of humanitarian operations during the pre-disaster has led researchers to develop various frameworks and methodologies. Campbell and Jones (2011) attempted to optimize the location for stocking relief supplies considering the risk of the location being very near to and/or too far from disaster sites. The impact of these risks on costs and stocking quality has been analyzed. They found that prepositioning of these distribution centers and pre-stocking of relief supplies can improve the overall effectiveness of disaster response. Given this, Noyan (2012) proposed a two-stage stochastic program to minimize the risk which arises from the uncertainty in several parameters while planning for response facility locations and the inventory levels of the relief supplies at each facility. Using sensitivity analysis, the effect of different risk measurements on optimal solutions is examined. Kelle et al. (2014) proposed a model to jointly optimize the prepositioning and response costs in response to a hurricane. Rezaei-Malek et al. (2016) proposed a model that determines the location of pre-positioning sites and optimize the ordering policy for perishable items that are stocked at these sites during the pre-disaster stage.

Another important decision in the disaster preparedness stage is the prepositioning of emergency shelters to immediately transfer the affected population during and after a disaster to minimize the post-disaster casualties. In this direction, Akgün et al. (2015) developed an optimization model to preposition the emergency supplies by minimizing the risk for a demand point. The vulnerability of the demand point, especially when it is not supported by the located facilities, is captured using fault tree analysis. Bayram et al. (2015) proposed a mixed-integer nonlinear programming (MINLP) model to identify the location, quantity, and planned capacity of emergency shelters to minimize the total evacuation time. Kilci et al. (2015) also modeled the site identification problem for emergency shelters considering a wide range of criteria, such as distance from health institutions, shelter construction and site type, site utilities, land type, and land ownership. Paul and MacDonald (2016) proposed a stochastic model to develop the capacity given a potential disaster risk, considering several factors such as casualty estimates, transportation tine, demographic factors, and demand clusters. Recently, Erbeyoğlu and Bilge (2020) proposed a model to design a pre-disaster relief network by locating storage and distribution centers in a way that the service adequacy and fairness at different demand points are maximized.

2.2 Review of disaster response

This subsection reviews the literature on a disaster response stage in humanitarian logistics, focusing on the evacuation of affected people from disaster sites to pre-determined shelters, distribution of relief supplies to the affected population, allocation of vehicles, and determining routes to minimize the response time and hence improving the overall effectiveness of disaster response.

Özdamar et al. (2004) proposed a multi-commodity vehicle routing model for optimizing the mix of commodities to be picked up in optimal quantities and the routes for the vehicles. The role of food and medical inventory is crucial in disaster relief. Whybark (2007) reviewed the inventory models for disaster relief supply chains considering the acquisition, storage, and distribution of inventory items. Sheu (2007) proposed a methodology for dynamic demand management during emergency logistics by considering demand forecast from multiple areas, clustering the affected areas into groups, and finally prioritizing these groups to optimize the resource allocation.

Route planning is another key challenge in humanitarian logistics. Campbell et al. (2008) proposed a modified set of objective functions for traveling salesman and vehicle routing problems to minimize the maximum arrival time and the average time. Holguín-Veras et al. (2012) argued that commercial and humanitarian logistics activities are very different. There is a need to separate long-term disaster recovery activities—which are similar to commercial logistics—from emergency disaster response and other short-term activities due to their different operational environments. Lin et al. (2012) proposed a location-allocation problem to identify the optimal number of temporary depot locations and vehicles to provide relief in case of an earthquake by minimizing the total costs of operations. Najafi et al. (2013) proposed a multi-objective stochastic model to provide emergency response in case of an earthquake by jointly optimizing evacuation of victims and distribution of relief supplies. In a similar study, Bish et al. (2014) modeled the emergency evacuation problem where the evacuation vehicles, healthcare, and medical facilities are proactively allocated to minimize the expected risk. Jin et al. (2015) considered the survival probabilities and proposed a logistics model for the evacuation of victims, in which the number of survivors is maximized. Duque et al. (2016) investigated dissatisfaction among the rescued people particularly due to delays in the delivery of goods during the emergency facility distribution.

Some studies jointly modeled the distribution route planning and allocation of relief supplies to various demand points to optimally utilize the vehicle and route capacities. For instance, Khayal et al. (2015) developed a mathematical model to optimize the distribution of temporary facilities and allocation of resources, aiming to minimize the deprivation cost. In a similar attempt, Cavdur et al. (2016) proposed a two-stage model to optimize the temporary disaster response facilities in the first stage and to optimize the distribution of relief items by minimizing the total distance traveled and resultant unmet demand costs in the second stage. Alem et al. (2016) developed a stochastic two-stage network model for the distribution of humanitarian aids to the victims, considering the practical constraints, such as budget, size, and number of vehicles, and varying procurement lead times. Pérez-Rodríguez and Holguín-Veras (2016) proposed a model for optimal assignment and routing of relief supplies in a post-disaster scenario, aiming to minimize the social costs of deprivation. Liu et al. (2019) proposed a multi-period, multi-item model to optimize the distribution of relief supplies to the injured population by minimizing the unmet demand, considering both demand and supply uncertainties.

The major challenge in humanitarian logistics is the scale of the disaster and limited road capacity. To overcome these challenges, Pyakurel et al. (2019) modeled the contraflow problem that optimizes the routes during evacuation operations. Emergency relief routing optimization often requires prioritization based on resource constraints. To address this, Zhu et al. (2019) proposed an emergency routing model to transfer the disaster victims with diverse injured degrees in the presence of capacity restrictions, aiming to minimize both operational costs and psychological sufferings. Sharma et al. (2019) developed a model for locating the temporary blood banks during a disaster to serve the hospitals with the minimum response time. In a recent study, Vries and Wassenhove (2020) highlighted that despite the extensive research in humanitarian operations, the existing models are rarely used in real practice. The primary reasons are found to be the huge variation in operational uncertainty and the costs involved in route optimization systems. It is suggested that rather than employing rigorous models with a focus on accuracy, relevant models that are capable to generate feasible options under operational uncertainty must be proposed.

2.3 Review on coordination and integration models

Although the previous disaster preparedness studies have developed theoretical insights to reduce the impacts of natural and man-made disasters, the overall effectiveness of disaster relief can be hampered by poor management and coordination between several stages and actors of the decentralized humanitarian supply chain (Özdamar et al., 2004). While coordination mechanisms in commercial supply chains are well studied (Asian & Nie, 2014), coordinating humanitarian supply chains are rather underexplored. Balcik et al. (2010) examined the challenges in humanitarian supply chain coordination and identified coordination as a key factor to achieve efficiency in relief logistics. Sazvar et al. (2021) integrated the sustainable closed-loop pharmaceutical supply chain with the vehicle routing problem with simultaneous pickup and delivery in a competitive market. They presented a mathematical model to find the potential locations for remanufacturers and disposal centers.

Coordinating the efforts of individual agencies that work at various levels improves the overall effectiveness of humanitarian logistics. Because of this, Zokaee et al. (2016) proposed a three-level relief distribution model by integrating the suppliers, distribution center, and demand points to minimize the overall costs of the entire relief chain. The satisfaction among the affected people is also captured by considering penalties on the shortages. Fikar et al. (2016) proposed a decision-making framework to coordinate the relief distribution efforts of private and relief bodies. A last-mile distribution model is proposed to optimize the routes considering open or closed roads, off roads, and unmanned aerial vehicles. Tofighi et al. (2016) proposed a relief distribution model that identifies the prepositioning of warehouses and distribution centers for locating the relief supplies and optimizing the transportation activities during the disaster, considering the inherent uncertainties in supply, demand, and availability of transportation routes in case of an earthquake. He and Zhuang (2016) studied the trade-offs between disaster preparedness and response stages and proposed a model that optimally allocates resources during pre-disaster and post-disaster operations. Toyasaki et al. (2017) suggested horizontal cooperation among various agencies in managing an inventory of relief supplies by strategically locating the depots. Rodríguez-Espíndola et al. (2018) proposed a disaster preparedness model to prevent human and material convergences. Such models can be useful in collaborative environments, in which where several organizations are working towards disaster relief.

Despite the extensive research in disaster preparedness, Goldschmidt and Kumar (2019) highlighted that there is a serious misalignment between key actors at various stages of a humanitarian supply chain. It is claimed that investments in disaster planning and preparedness do not always lead to efficient disaster relief when evaluated based on the response time, overall costs of relief, and the number of affected people. Such disconnect between disaster planning and disaster response stages can be addressed through the integrated planning of these activities and increased coordination between various actors. Dubey et al. (2019a) identified the lack of coordination and information sharing between various agencies during the emergency response and disaster planning as a major challenge leading to duplication of efforts, wastage of resources, and insufficient supply of aid, thus adding to the suffering of the affected population. To ensure the collaborative performance of disaster relief bodies, the role of big data analytics capability is studied by Dubey et al. (2019b). Sabouhi et al. (2019) proposed an integrated evacuation and distribution model that jointly optimizes routing and scheduling of vehicles. The goal is to evacuate people from affected areas to shelters and distribute necessary relief commodities, considering limited vehicle capacity and split delivery options. With the recent increase in the use of disruptive technologies in decision making, Dubey et al. (2020a, b) studied the effect of information sharing, supply chain visibility, and the potential role of blockchain technology in ensuring trust and collaborative relationship among various humanitarian actors.

2.4 Review of the solution methods

Due to the scale of the problem and the number of variables involved, humanitarian logistics models are known to be computationally complex. Prior studies showed that, when employing exact solvers (e.g., CPLEX, LINGO), computational time to solve these models is highly sensitive to the problem size.

Li et al. (2012) employed the CPLEX solver to solve a two-stage disaster relief problem and found that while the numerical illustrations for medium-sized problems can be solved in a feasible time, the computational time increases exponentially for larger problems. Tricoire et al. (2012) employed the ε-constraint method to solve the multi-objective problem for disaster relief. Using the multiple iterations, an optimal Pareto front was generated and a maximum optimality gap of 70% was reported. Li et al. (2012) employed the Lagrangian function to solve a stochastic two-stage humanitarian planning problem, which was developed as a bi-level model. Given the concavity of the Lagrangian dual problem, a heuristic linear search algorithm was developed. Tofighi et al. (2016) proposed a fuzzy multi-objective model for disaster relief and employed a differential evolution algorithm to solve the problem. The optimality gap of 1.89% in comparison to the optimal solution was reported. The main limitation of this model is that the performance of the obtained solution depends on the parameters that are selected based on the trial-and-error method. Hence, it might take a couple of hours to solve a real case study using their proposed method.

Researchers have developed several heuristics and meta-heuristics to tackle the complexity of large-scale real-world problems (Faghih-Roohi et al., 2016; Paul et al. 2019; 2018; Somarin et al., 2016; Rezaei Somarin et al., 2017; 2018). Saeidian et al. (2016) considered the coverage of urban areas in a disaster scenario caused by an earthquake. They proposed a genetic algorithm (GA) and a bee algorithm (BA) to tackle the complexity of their large-scale optimization problem in finding the optimal location of relief centers. Bozorgi-Amiri et al. (2012) developed a particle swarm optimization (PSO) algorithm and obtained solutions with an average optimal gap of 4.1% for the small- and medium-sized problems. However, their developed heuristic was not able to perform well for the large-scale problems in terms of solution time. Rath and Gutjahr (2014) developed a math-heuristic for a three-objective warehouse location–routing problem in disaster relief. The proposed technique was developed based on an adaptive ε-constraint algorithm, where the constraints were generated on demand by a variable neighborhood search (VNS) algorithm and stored in a constraint pool. Onan et al. (2015) proposed a multi-objective optimization model to identify the locations of temporary storage facilities and planning for collection and transportation of the disaster waste in an environmentally sustainable manner. The proposed model was solved using an evolutionary elitist multi-objective optimization algorithm (NSGA-II). Memari et al. (2018) proposed a fuzzy dynamic location-allocation model for disaster response using queuing theory. The augmented ε-constraint method and NSGA-II were used to solve and validate the model. They have used the NSGA-II in a large-scale case study and found the quality of the Pareto-optimal solution to be high.

3 Research gaps and research objectives

Table 1 provides a summary of the reviewed literature. Our extensive literature review indicates that the humanitarian logistics area has received considerable attention from both academicians and researchers over the last two decades. It is observed that the majority of the prior studies focus on either pre-disaster and post-disaster stages and only consider one aspect of humanitarian logistics, such as inventory planning, evacuation planning, or relief distribution. In a real-case scenario, however, all these decisions are interrelated and interdependent in nature and need to be planned simultaneously.

Considering the importance of the pre-disaster preparation phase and its direct impact on disaster response, some studies proposed integrated location-allocation models that jointly optimizes the location identification for emergency shelters (or relief distribution centers) and the evacuation of people (or distribution of relief supplies). However, only a few papers focus on developing integrated humanitarian logistics considering all stages of disaster relief into consideration. This gap results in the lack of coordination in various humanitarian activities which has been also highlighted as a major research gap in some recent papers.

To address these shortcomings, this paper has three research objectives:

RO1 To optimally identify the locations of emergency shelters and depots in the pre-disaster stage;

RO2 To optimally plan a resource allocation-route planning integrated model for the evacuation of people from the disaster zone to the emergency shelters during disaster response and considering demand uncertainty;

RO3 To model the coordinated distribution of relief supplies from the depots to the emergency shelters such that distributive injustice and dissatisfaction costs are minimized.

4 Problem statement and model formulation

4.1 Problem statement

This study integrates the various operations that are carried out in the pre-disaster planning and during disaster response stages, aiming to propose an integrated and coordinated humanitarian logistics model. The research framework developed to approach the described problem is shown in Fig. 1.

During the disaster response stage, the rescued people need to be immediately evacuated from the disaster sites to the pre-determined shelters via emergency vehicles. The number

Table 1 A summary of reviewed literature

Studies	Disaster preparation			Disaster response					Nature of study	
	Shelter location	Depot location	Inventory planning	Evacuation planning	Relief distribution	Vehicle planning	Route planning	Coordination	Conceptual	Mathematical
Holguín-Veras et al. (2012)									*	
Li et al. (2012), Bayram et al. (2015)	*			*		*				*
Kovács and Spens (2009), Balcik et al. (2010), Gunasekaran et al. (2018), Dubey et al. (2019a, b)								*	*	
Sheu (2007)					*		*			*
Campbell and Jones (2011), Kilci et al. (2015)	*									*
Lin et al. (2012)	*									*
Bozorgi-Amiri et al. (2012)					*	*	*			*
Li et al. (2012)	*				*		*			
Davis et al. (2013)			*					*		*
Najafi et al. (2013)				*	*					*
Bish et al. (2014)				*		*				*
Cavdur et al. (2016)		*								*
Whybark (2007), Falasca and Zobel (2011), Jin et al. (2015)			*							*
Pyakurel et al. (2019)				*			*			*
Kelle et al. (2014), Akgün et al. (2015), Rezaei-Malek et al. (2016)		*			*					*
Özdamar et al. (2004)					*		*	*		*
Fikar et al. (2016)					*			*		*
Tofighi et al. (2016)		*			*					*

Table 1 (continued)

Studies	Disaster preparation			Disaster response					Nature of study	
	Shelter location	Depot location	Inventory planning	Evacuation planning	Relief distribution	Vehicle planning	Route planning	Coordination	Conceptual	Mathematical
He and Zhuang (2016)		*			*			*		*
Paul and MacDonald (2016)	*		*		*					*
Duque et al. (2016), Khayal et al. (2015)		*			*					*
Alem et al. (2016)						*	*			*
Pérez-Rodríguez and Holguín-Veras (2016)			*		*					*
Onan et al. (2015)		*			*					
Rath and Gutjahr (2014)		*			*					
Tricoire et al. (2012), Faghih-Roohi et al. (2016), Zhu et al. (2019)							*			*
Toyasaki et al. (2017)			*					*		*
Rodríguez-Espíndola et al. (2018)		*						*		*
Ni et al. (2018)		*	*							*
Memari et al. (2018)					*					*
Zokaee et al. (2016), Zahiri et al. (2017)					*					*
Raziei et al. (2018)					*		*			*
Goldschmidt and Kumar (2019)	*			*					*	
Sabouhi et al. (2019)				*	*	*		*		*
Erbeyoğlu and Bilge (2020)		*			*					*

Table 1 (continued)

Studies	Disaster preparation			Disaster response					Nature of study	
	Shelter location	Depot location	Inventory planning	Evacuation planning	Relief distribution	Vehicle planning	Route planning	Coordination	Conceptual	Mathematical
Proposed model	.*	m*	*	m*	m*	m*	*	n*		n*

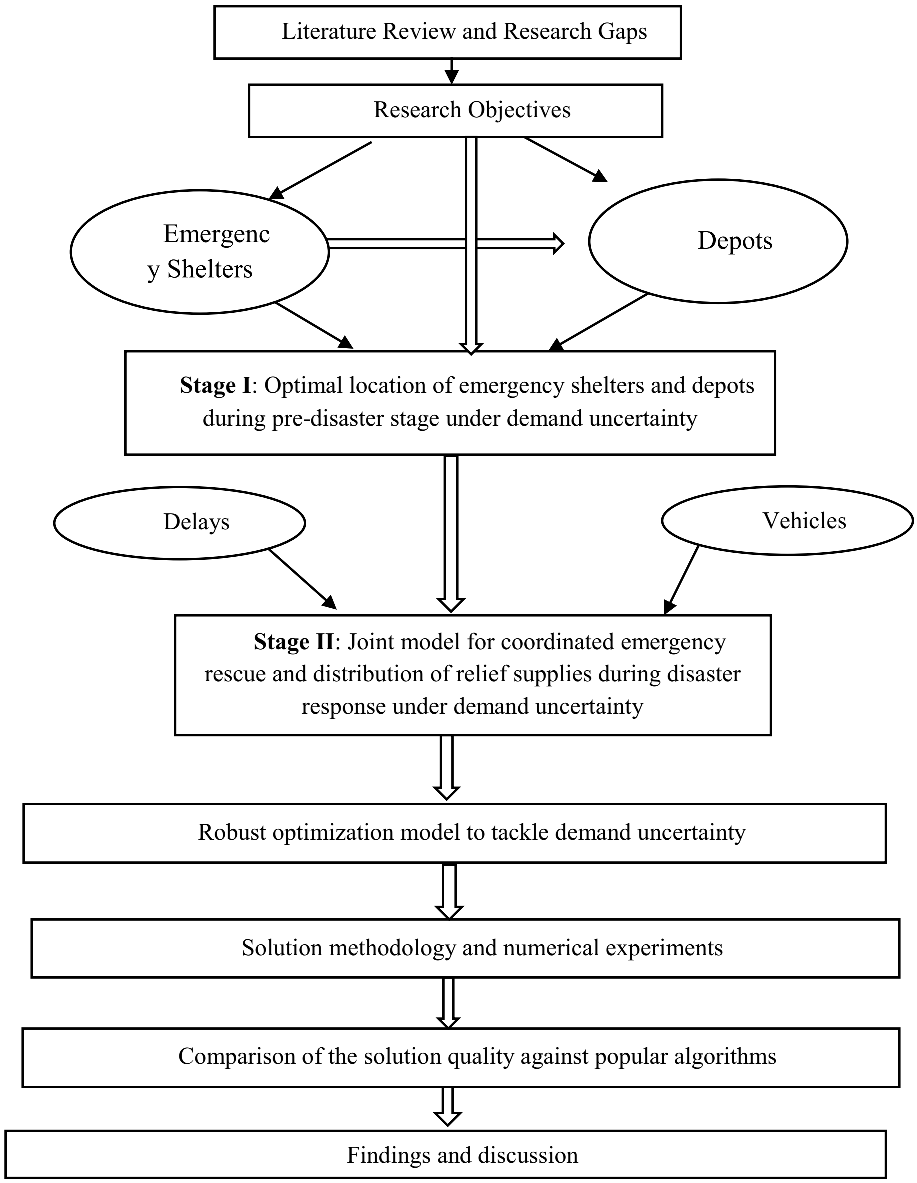


Fig. 1 Research framework

of required vehicles and the routes to be followed need to be optimized in such a way that a maximum number of people can be evacuated. Once the rescued people are transferred to the emergency shelters, there is a need to provide them with the optimal amount of essential relief supplies, such as tents, drinking water, food, and first aid kits in a reasonable time. Therefore, it is required to plan for the emergency vehicles to collect enough quantities of the relief supplies from the depots to the emergency shelters at regular time intervals in coordination with the evacuation operations. Any delay in delivery is likely to negatively influence the relief operations and may cause dissatisfaction among the disaster victims as well as aid providers. The uncertainty in the demand for the essential goods at the emergency shelters must be taken into consideration while stocking the depots before and after the disaster. It must be ensured that the rescue operations promote a sense of fairness and satisfaction to the rescued people and meet their needs in a cost-efficient manner.

To address the above concerns, this paper makes a novel attempt to integrate the evacuation and relief distribution operations in a two-stage model, aiming to coordinate the disaster response activities and minimize the distributive injustice and dissatisfaction costs.

4.2 Model formulation: two-stage MO-MINLP

In this section, a two-stage mathematical model is proposed for coordinating disaster planning and disaster relief activities. In the first stage, the model optimally identifies the locations for emergency shelters and depots based on the required travel time. In the second stage, the model jointly optimizes the distribution network of the relief supplies from the depots to the emergency shelters in a coordinated manner such that the demand coverage is maximized, and potential dissatisfaction and distributive injustice costs are minimized. The model incorporates the permissible and impermissible delays in the delivery of essential goods. Each type of delay is associated with a specific penalty weight based on the importance of delivery timeliness to ensure that relief supplies are received at emergency shelters within the given time window.

The sets, indices, parameters, and decision variables used in the formulation of the two-stage mathematical model are presented below:

Sets and indices

$j \in \{1, 2, \ldots, J\}$	Critical areas
$i \in \{1, 2, \ldots, I\}$	Candidate sites for a shelter construction
$m \in \{1, 2, \ldots, M\}$	Required vehicle type for evacuation from critical areas
$p \in \{1, 2, \ldots, P\}$	Depots
$k \in \{1, 2, \ldots, K\}$	Routes
$h \in \{1, 2, \ldots, H\}$	Hospitals
$n \in \{1, 2, \ldots, N\}$	Goods type
$t \in \{1, 2, \ldots, \tau\}$	Period
$l \in \{1, 2, \ldots, L\}$	Required vehicle number for goods transportation from depots to shelters

Parameters

$K1_{ij}$	Number of routes between shelter i and critical area j
Cap_i	Total capacity of shelter i
$c1_m$	Capacity of the vehicle type m to carry non-admitted patients
$c2_m$	Capacity of the vehicle type m to carry admitted patients
PH_j	Probability of being non-admitted patients in critical area j
d_{pi}	Distance between depot p and shelter i
d'_{jik}	Distance between critical area j and shelter i from route k
d_i^h	Distance between shelter i and hospital h
d_i^R	Distance between shelter i and the main road

DistHealth	Maximum allowed distance between shelters and health centers
DistRoad	Maximum allowed distance between shelters and the main road
Distance	Maximum allowed distance to exit people from critical areas and reach shelters
β	Minimum percent of total capacity required to establish shelters
α	Maximum acceptable percentage of people to open shelters of other candidates
DE_j	Total demand in critical area j to evacuate the area
Q_j	Number of vehicles in critical area j
UI	Upper bound for the number of shelters that can be established
LP	Lower bound for the number of depots assigned to each shelter
UP	Upper bound for the number of depots assigned to each shelter
μ	Upper bound for the total number of temporary depots
we_i	Weight factor of candidate site i for shelter establishment
we'_p	Weight factor of the p-th depot for the establishment
$K2_{ip}$	Number of routes between shelter i and depot p
ξ_p	Total number of vehicles in depot p including vehicles on the way and stationary vehicles
T	Subset of time that goods are delivered from depots to shelters without delay
T'	Subset of time that is allowed for delivery of goods from depots to shelters with delay
T^{ε}	Subset of time that is not allowed for delivery of goods from depots to shelters with delay
WP_n	Weight of each good from type n
VP_n	Volume of each good from type n
ϖ	Maximum weight capacity of load per truck
υ	Maximum volume capacity of load per truck
W_1	Weight factor of people's dissatisfaction in case of receiving goods with allowed delay time
W_2	Weight factor of people's dissatisfaction in case of receiving goods with delay time that is not allowed
W_3	Weight factor of traveling from depots to shelters
W_4	Weight factor of injustice in goods distribution
CT_{pik}	Cost of travel from depot p to shelter i through route k
PL_n	Penalty cost for goods delivery to shelters with the allowed delay time
FP_n	Penalty cost for goods delivery to shelters with the delay time that is not allowed
J'_p	Cost of stationary vehicles in depots
U_{pn}	Amount of goods with type n that are available in depot p
TR_{pkli}	Required time for vehicle l to send from depot p to shelter i through route k
BN	Large number (its value is 100000 in this study)

Decision variables

y_p	1 if depot p is established for assigning goods; 0, otherwise
x_i	1 if candidate site i is selected for shelter construction; 0, otherwise
V_{jik}	Percentage of people in critical area j who are transferred to shelter i through route k
X'_{pi}	1 if the candidate site is assigned to depot p for shelter construction; 0, otherwise
a_{jik}	Number of the required vehicles for transferring people from critical area j to shelter i through route k
y'_{jim}	1 if people are assigned from critical area j to shelter i by vehicle type m; 0, otherwise
X^{ε}_{pniklt}	Amount of goods of type n transferred at time t to cover the demand of shelter i from depot p through route k and with vehicle number l
Y^{ε}_{piklt}	1 if there is a delivery from depot p through route k with lth vehicle to shelter i at time t
S'_i	Dissatisfaction cost of shelter i

σ_p Number of vehicles in depot p

4.2.1 Stage (I) model

The first objective function of the proposed two-stage multi-objective model is shown in Eq. (1), representing the location decisions for the emergency shelters and depots such that the suitability of the site is maximized. The second objective is shown in Eq. (2) which tends to minimize the total distance between the depots and emergency shelters.

$$\text{Max } Z1 = \sum_{i=1}^{I} we_i x_i - \sum_{p=1}^{P} we'_p y_p \tag{1}$$

$$\text{Min } Z2 = \sum_{i=1}^{I}\sum_{p=1}^{P} d_{pi} X'_{pi} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K1_{ij}} d'_{jik} DE_j\, V_{jik} \tag{2}$$

subject to :

$$\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{k=1}^{K1_{ij}} DE_j\, y'_{jim} V_{jik} \ge \beta\, Cap_i\, x_i; \quad \forall i \tag{3}$$

$$\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{k=1}^{K1_{ij}} DE_j\, y'_{jim} V_{jik} \le Cap_i\, x_i; \quad \forall i \tag{4}$$

$$d_i^h x_i \le DistHealth; \quad \forall i, h \tag{5}$$

$$d_i^R x_i \le DistRoad; \quad \forall i \tag{6}$$

$$\frac{\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{k=1}^{K1_{ij}} DE_j\, y'_{jim} V_{jik}}{Cap_i} - \frac{\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{k=1}^{K1_{i'j}} DE_j\, y'_{ji'm} V_{ji'k}}{Cap_{i'}} \le \alpha + \left(1 - x_i\right) + \left(1 - x_{i'}\right); \quad \forall i \ne i' \in I \tag{7}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K1_{ij}} V_{jik} = 1; \quad \forall j \tag{8}$$

$$\sum_{k=1}^{K1_{ij}} V_{jik} \le \sum_{m=1}^{M} y'_{jim}; \quad \forall i, j \tag{9}$$

$$\sum_{j=1}^{J} y'_{jim} \leq x_i; \quad \forall i, m \tag{10}$$

$$\sum_{i=1}^{I} x_i \leq UI \tag{11}$$

$$\sum_{k=1}^{K1_{ij}} d'_{jik} y'_{jim} \leq Distance; \quad \forall i, j, m \tag{12}$$

$$a_{jik} \geq \sum_{m=1}^{M} \left\{ PH_j \frac{DE_j\, V_{jik}}{c1_m} + \left(1 - PH_j\right) \frac{DE_j\, V_{jik}}{c2_m} \right\}; \quad \forall i, j, k, m \tag{13}$$

$$\sum_{i=1}^{I} \sum_{k=1}^{K1_{ij}} a_{jik} \leq Q_j; \quad \forall j \tag{14}$$

$$a_{jik} \leq Q_j \sum_{m=1}^{M} y'_{jim}; \quad \forall i, j, k \tag{15}$$

$$LP \leq \sum_{p=1}^{P} X'_{pi} \leq UP; \quad \forall i \tag{16}$$

$$\sum_{p=1}^{P} y_p \leq \mu \tag{17}$$

$$\sum_{i=1}^{I} X'_{pi} \leq BN\, y_p; \quad \forall p \tag{18}$$

$$\sum_{p=1}^{P} X'_{pi} \leq BN\, x_i; \quad \forall i \tag{19}$$

$$\sum_{k=1}^{K1_{ij}} DE_j\, V_{jik} \leq BN \sum_{m=1}^{M} y'_{jim}; \quad \forall i, j \tag{20}$$

Constraint (3) presents the minimum utilization rate required for each emergency shelter. Constraint (4) presents the allocation of disaster victims from affected areas to each shelter, subject to shelters' capacity. Constraints (5) and (6) present a candidate site for shelter establishment with the consideration of the minimum allowed distance from a health center to the main roads. Constraint (7) ensures the balance between the allocated population under the shelter establishment condition. Constraint (8) assures that everyone is evacuated from the critical areas. Constraint (9) ensures that disaster victims will be allocated to emergency shelters, only if there is a response to their evacuation needs from critical areas. Constraint (10) presents the open shelters to which affected people can be immediately transferred from the critical areas. Constraint (11) assures that the number of shelters is lower than the maximum threshold (set based on the budget limits, planning, etc.). Constraint (12) guarantees that the traveled distance between critical areas and shelters is less than a specified upper bound.

Constraint (13) assures that demands for evacuating people from critical areas to the shelters are lower than the number of allocated vehicles. Constraint (14) ensures that the number of vehicles in each affected area covers the demand of that area. Constraint (15) guarantees that vehicle destination from the critical area is always a pre-selected emergency shelter. Constraints (16) assures that the number of depots allocated to each emergency shelter satisfies the pre-determined lower and upper bounds. Constraint (17) presents the maximum number of depots that can be established. Constraints (18) ensures that there always exists a depot for each shelter. Constraint (19) presents that the demand for open shelters is always satisfied by depots. Constraint (20) ensures that healthy and injured people are evacuated and allocated to emergency shelters.

4.2.2 Stage (II) model

The second stage of the proposed model optimizes the distribution of relief supplies from depots to the emergency shelters to improve the overall coordination between these activities. Equation (21) presents the objective function of the problem which minimizes the total penalty costs for the relief supplies delivered to the emergency shelters considering permissible and impermissible delay time. It also minimizes the total cost of travel from depots to the emergency shelters and the total cost of distributive injustice and unutilized vehicles in depots.

$$\begin{aligned}\text{Min } Z3 = W_1 &\left\{ \sum_{p=1}^{P} \sum_{n=1}^{N} \sum_{i=1}^{I} \sum_{k=1}^{K2_{ip}} \sum_{l=1}^{\xi_p} \sum_{t \in T\prime} PL_n \, X''_{pniklt} \right\} \\ &+ W_2 \left\{ \sum_{p=1}^{P} \sum_{n=1}^{N} \sum_{i=1}^{I} \sum_{k=1}^{K2_{ip}} \sum_{l=1}^{\xi_p} \sum_{t \in T''} FP_n \, X''_{pniklt} \right\} \\ &+ W_3 \left\{ \sum_{p=1}^{P} \sum_{i=1}^{I} \sum_{k=1}^{K2_{ip}} \sum_{l=1}^{\xi_p} \sum_{t=1}^{\tau} CT_{pik} \, Y''_{piklt} \right\} + W_4\{S\} + \left\{ \sum_{p=1}^{P} \sigma_p \, J'_p \right\}\end{aligned} \tag{21}$$

s.t.

$$\sigma_p \le \xi_p y_p; \quad \forall p \tag{22}$$

$$\sigma_p \le \xi_p - max\left\{ \frac{\sum_{n=1}^{N} \sum_{i=1}^{I} WP_n X^{\varepsilon}_{pniklt}}{\varpi}, \frac{\sum_{n=1}^{N} \sum_{i=1}^{I} VP_n X^{\varepsilon}_{pniklt}}{\upsilon} \right\}; \quad \forall p, l, t, k \in K2_{ip} \tag{23}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K2_{ip}}\sum_{l=1}^{\xi_p}\sum_{t=1}^{\tau} Y^{\varepsilon}_{piklt} \le BNy_p; \quad \forall p \tag{24}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K2_{ip}} TR_{pkli} Y^{\varepsilon}_{piklt} \le \tau \quad \forall p, t, ; \quad \forall l \in \xi_p \tag{25}$$

$$X^{\varepsilon}_{pniklt} \le BNY^{\varepsilon}_{piklt} \quad \forall p, t, i, n, ; \quad \forall l \in \xi_p, k \in K2_{ip} \tag{26}$$

$$\sum_{p=1}^{P}\sum_{k=1}^{K2_{ip}}\sum_{l=1}^{\xi_p} X^{\varepsilon}_{pniklt} \ge \sum_{k=1}^{K1_{ij}}\sum_{j=1}^{J} DE_j\, V_{jik}; \quad \forall n, i, t \tag{27}$$

$$\sum_{n=1}^{N}\sum_{i=1}^{I} WP_n\, X^{\varepsilon}_{pniklt} \le \varpi; \quad \forall p, t \quad \forall k \in K2_{ip}, l \in \xi_p \tag{28}$$

$$\sum_{n=1}^{N}\sum_{i=1}^{I} VP_n\, X^{\varepsilon}_{pniklt} \le \upsilon; \quad \forall p, t \quad \forall k \in K2_{ip}, l \in \xi_p \tag{29}$$

$$\sum_{k=1}^{K2_{ip}}\sum_{l=1}^{\xi_p} X^{\varepsilon}_{pniklt} \le U_{pn} X'_{pi}; \quad \forall p, n, i, t \tag{30}$$

$$S'_i = \sum_{p=1}^{P}\sum_{n=1}^{N}\sum_{k=1}^{K2_{ip}}\sum_{l=1}^{\xi_p}\sum_{t\in T'} PL_n\, X^{\varepsilon}_{pniklt} + \sum_{p=1}^{P}\sum_{n=1}^{N}\sum_{k=1}^{K2_{ip}}\sum_{l=1}^{\xi_p}\sum_{t\in T^{\varepsilon}} FP_n\, X^{\varepsilon}_{pniklt}; \quad \forall i \tag{31}$$

$$S = \max\{S'_i\} - \min\{S'_i\} \tag{32}$$

$$y_p, x_i, X'_{pi}, y'_{jim}, Y^{\varepsilon}_{piklt} \in \{0,1\}, a_{jik}, X^{\varepsilon}_{pniklt}, \sigma_p \in \mathbb{Z}^+, V_{jik}, S, S'_i \ge 0; \quad \forall p, i, j, m, k, l, t, n \tag{33}$$

Constraint (22) indicates that the number of the allocated vehicles to each depot must be larger than the number of vehicles required for open depots. Constraint (23) calculates the number of idle vehicles in depots by considering the number of vehicles used in each depot for emergency goods delivery. Constraint (24) states that the origin of transporting vehicles are open depots. Constraint (25) ensures that the total delivery time of relief goods to shelters is less than the total duration of the operations time. Constraint (26) ensures that an emergency shelter's demand will be satisfied only if vehicles depart from depots. Constraint (27) guarantees that shelters' demands for receiving relief supplies will be satisfied. Constraints (28) and (29) present the weights and volume of the delivered goods from depots considering the capacity of delivery vehicles. Constraint (30) indicates that a depot will cover a shelter's demand only if the shelter is allocated to the depot. Constraint (31) calculates the dissatisfaction caused by the lack of shelters' demand coverage. Constraint (32) calculates the distributive injustice measure resulted from the dissatisfaction at each shelter. Finally, Constraint (33) refers to the decision variables of the proposed model.

4.2.3 Linearization of the proposed two-stage MO-MINLP into MO-MILP

After formulating the mathematical model, non-linear equations are linearized. Constraints (3), (4) and (7) are originally defined as non-linear functions of y'_{jim} and V_{jik} variables. To linearize these Constraints, a new variable VY_{jimk} is defined as $VY_{jimk} = V_{jik} \times y'_{jim}$. Hence, considering the binary nature of y'_{jim} variable, the linearization can be presented as follows:

$$V_{jik} \times y'_{jim} \leq VY_{jimk}; \quad \forall j, i, m, k \tag{34}$$

$$VY_{jimk} \leq y'_{jim}; \quad \forall j, i, m, k \tag{35}$$

$$VY_{jimk} \geq 0; \quad \forall j, i, m, k \tag{36}$$

Therefore, Constraints (3), (4) and (7) can be transformed to the following equations:

$$\sum_{m=1}^{M} \sum_{j=1}^{J} \sum_{k=1}^{K1_{ij}} DE_j \; VY_{jimk} \geq \beta \; Cap_i \; x_i; \quad \forall i \tag{37}$$

$$\sum_{m=1}^{M} \sum_{j=1}^{J} \sum_{k=1}^{K1_{ij}} DE_j \; VY_{jimk} \leq Cap_i \; x_i; \quad \forall i \tag{38}$$

$$\begin{aligned} &\frac{\sum_{m=1}^{M} \sum_{j=1}^{J} \sum_{k=1}^{K1_{ij}} DE_j \; VY_{jimk}}{Cap_i} - \frac{\sum_{m=1}^{M} \sum_{j=1}^{J} \sum_{k=1}^{K1_{i'j}} DE_j \; VY_{ji'mk}}{Cap_{i'}} \\ &\leq \alpha + \left(1 - x_i\right) + \left(1 - x_{i'}\right); \quad \forall i \neq i' \in I \end{aligned} \tag{39}$$

Constraint (23) can also be linearized by adding the following three equations:

$$WVP_{pklt} \geq \frac{\sum_{n=1}^{N} \sum_{i=1}^{I} WP_n X^{\varepsilon}_{pniklt}}{\varpi}; \quad \forall p, l, t, k \in K2_{ip} \tag{40}$$

$$WVP_{pklt} \geq \frac{\sum_{n=1}^{N} \sum_{i=1}^{I} VP_n X^{\varepsilon}_{pniklt}}{\upsilon}; \quad \forall p, l, t, k \in K2_{ip} \tag{41}$$

$$WVP_{pklt} \geq 0; \quad \forall p, l, t, k \in K2_{ip} \tag{42}$$

Thus, Constraint (23) is transformed to the following alternative equation:

$$\sigma_p \leq \xi_p - WVP_{pklt}; \quad \forall p, l, t, k \in K2_{ip} \tag{43}$$

Finally, Constraint (32), which is the subtraction of the maximum and minimum value of the set S'_i, is linearized by adding *SMX* and *SMN* variables.

$$SMX \geq S'_i; \quad \forall i \tag{44}$$

$$SMN \geq -S'_i; \quad \forall i \tag{45}$$

$$S = SMX + SMN \tag{46}$$

$$SMX \geq 0, SMN \leq 0 \tag{47}$$

4.2.4 Robust optimization for demand uncertainty

Robust optimization techniques are developed to deal with complexities caused by a range of uncertainty factors. They enable us to search for near-optimal solutions and maintain their feasibility with a high probability and offer the flexibility of extending the obtained optimal solution to a certain possible limit under an uncertain situation. To control and deal with different levels of required conservatism associated with the solutions of a proposed two-stage multi-objective problem under demand uncertainty, we use a robust optimization approach that was first introduced by Bertsimas and Sim (2004). For better illustration, we first explain the employed robust optimization framework. Consider the following optimization problem:

$$\begin{aligned} &\text{Min } c^T x \\ &\text{s.t. } \; Ax \leq b \\ &1 \leq x \leq u \end{aligned} \tag{48}$$

Now, assume that c^T and A constitute the uncertain parameters of the model. So, uncertainty intervals are considered as $[c_j - d_j, c_j + d_j]$ and $[a_{ij} - \widehat{a}_{ij}, a_{ij} + \widehat{a}_{ij}]$ for c^T and A, respectively. Here, d_j and $\widehat{a}_{ij}$ represent the deviation levels from the average values of parameters c_j and a_{ij}, respectively. In the next step, the final robust model can be developed by implementing the required transformations suggested by Bertsimas and Sim (2004):

$$
\begin{aligned}
&\min \quad c^T x + z_0\Gamma_0 + \sum_{j\in J_0} p_{0j} \\
&\text{s.t.} \\
&\sum_j a_{ij}x_j + z_i\Gamma_i + \sum_{j\in J_i} p_{ij} \le b_i \quad \forall i \\
&z_0 + p_{0j} \ge d_j y_j \quad \forall i \in J_0 \\
&z_i + p_{ij} \ge \hat{a}_{ij} y_j \quad \forall i \ne 0, j \in J_i \\
&p_{ij} \ge 0 \quad \forall i, j \in J_i \\
&y_j \ge 0 \quad \forall j \\
&z_i \ge 0 \quad \forall i \\
&-y_j \le x_j \le y_j \quad \forall j \\
&l_j \le x_j \le u_j, \quad \forall j
\end{aligned}
\tag{49}
$$

where z_0, p_{0j}, z_i, p_{ij} and y_j are the robustness variables. Moreover, Γ_0 and Γ_i are the conservatism levels (i.e., the budget of uncertainty) of the objective function and uncertain constraints, respectively.

To develop the robust counterpart of the proposed model in this paper, the parameter DE_j(i.e., the total demand for area j) is considered to be uncertain with an uncertainty interval of $[\widetilde{DE}_j - \widehat{DE}_j\ \widetilde{DE}_j + \widehat{DE}_j]$ for the total demand in critical area j. According to interval uncertainty, each uncertain value of $\underset{\sim}{DE}_j$ is considered in the form of a limited symmetric interval centered on DE_j as $\widehat{DE}_j = \alpha DE_j$, where DE_j is the estimated value of the demand parameter, $\widehat{DE}_j$ captures demand fluctuations, and $\alpha > 0$ is the parameter uncertainty level.

Since parameter uncertainty is reflected only in the constraints, the objective functions remain unchanged. However, Constraints (13), (20), (27), (37), (38) and (39) should be transformed into new constraints (Bertsimas & Sim, 2004):

$$
\begin{aligned}
a_{jik} \ge \sum_{m=1}^{M} \Bigg\{ & PH_j \frac{\widetilde{DE}_j\ V_{jik} + Z1_i\Gamma 1_i + \sum_m r1_{imjk}}{c1_m} \\
& + (1 - PH_j) \frac{\widetilde{DE}_j\ V_{jik} + Z2_i\Gamma 2_i + \sum_m r2_{imjk}}{c2_m} \Bigg\} \quad \forall i, j, k, m
\end{aligned}
\tag{50}
$$

$$
Z1_i + r1_{imjk} \ge \widetilde{DE}_j\ E1_j \quad \forall i, j, k, m \tag{51}
$$

$$
Z2_i + r2_{imjk} \ge \widetilde{DE}_j\ E2_j \quad \forall i, j, k, m \tag{52}
$$

$$
\sum_{k=1}^{K1_{ij}} \widetilde{DE}_j\ V_{jik} + Z3_i\Gamma 3_i + \sum_m \sum_k r3_{imjk} \le BN \sum_{m=1}^{M} y'_{jim} \quad \forall i, j \tag{53}
$$

$$
Z3_i + r3_{imjk} \ge \widetilde{DE}_j\ E3_j \quad \forall i, j, k, m \tag{54}
$$

$$\sum_{p=1}^{P}\sum_{k=1}^{K2_{ip}}\sum_{l=1}^{\xi_p} X''_{pniklt} - Z4_i\Gamma 4_i - \sum_{p}\sum_{k}\sum_{l}\sum_{j} r4_{pklj} \geq \sum_{k=1}^{K1_{ij}}\sum_{j=1}^{J} \widetilde{DE}_j\ V_{jik} \quad \forall n, i, t \tag{55}$$

$$Z4_i + r4_{pklj} \geq \widetilde{DE}_j\ E4_j \quad \forall i, \mathrm{p}, j, k, l \tag{56}$$

$$\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{k=1}^{K1_{ij}} \widetilde{DE}_j\ VY_{jimk} - Z5_i\Gamma 5_i - \sum_{m}\sum_{j}\sum_{k} r5_{imjk} \geq \beta\ \ Cap_i\ \ x_i \quad \forall i \tag{57}$$

$$Z5_i + r5_{imjk} \geq \widetilde{DE}_j\ E5_j \quad \forall i, j, k, m \tag{58}$$

$$\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{k=1}^{K1_{ij}} \widetilde{DE}_j\ VY_{jimk} + Z6_i\Gamma 6_i + \sum_{m}\sum_{j}\sum_{k} r6_{imjk} \leq Cap_i\ x_i \quad \forall i \tag{59}$$

$$Z6_i + r6_{imjk} \geq \widetilde{DE}_j\ E6_j \quad \forall i, j, k, m \tag{60}$$

$$\begin{aligned} &\frac{\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{k=1}^{K1_{ij}} \widetilde{DE}_j\ VY_{jimk} + Z7_i\Gamma 7_i + \sum_m\sum_j\sum_k r7_{imjk}}{Cap_i} \\ &\quad - \frac{\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{k=1}^{K1_{i\prime j}} \widetilde{DE}_j\ VY_{ji\prime mk} + Z8_i\Gamma 8_i + \sum_m\sum_j\sum_k r8_{imjk}}{Cap_{i\prime}} \\ &\leq \alpha + \left(1 - x_i\right) + \left(1 - x_{i\prime}\right) \quad \forall i \neq i\prime \in I \end{aligned} \tag{61}$$

$$Z7_i + r7_{imjk} \geq \widetilde{DE}_j\ E7_j \quad \forall i, j, k, m \tag{62}$$

$$Z8_i + r8_{imjk} \geq \widetilde{DE}_j\ E8_j \quad \forall i, j, k, m \tag{63}$$

$$\begin{aligned} &Z1_i, Z2_i, Z3_i, Z4_i, Z5_i, Z6_i, Z7_i, Z8_i \geq 0 \\ &r1_{imjk}, r2_{imjk}, r3_{imjk}, r4_{imjk}, r5_{imjk}, r6_{imjk}, r7_{imjk}, r8_{imjk} \geq 0 \\ &E1_j, E2_j, E3_j, E4_j, E5_j, E6_j, E7_j, E8_j \geq 0 \\ &\mu 1_i, \mu 2_i, \mu 3_i, \mu 4_i, \mu 5_i, \mu 6_i, \mu 7_i, \mu 8_i \in [0, 1] \end{aligned} \tag{64}$$

The proposed model has two objectives: (1) to find the optimal location of shelters and depots before a disaster. (2) to optimally distribute the post-disaster goods delivery considering the penalty costs, permissible and impermissible delay time, cost of travel from depots to shelters, cost of injustice, cost of stationary vehicles in depots, and the uncertainty of demand.

Table 2 NSGA-II parameters

Parameter	Definition
MaxIT	Maximum algorithm repetitions (i.e., termination condition)
nPop	Initial population
PCrossover	Crossover probability
PMutation	Mutation probability
Mu	Mutation rate
sigma	Mutation step size

Table 3 Factors of the Taguchi method and their different levels for the NSGA-II

Parameter	Level 1	Level 2	Level 3
MaxIT	100	150	200
nPop	100	150	200
PCrossover	0.6	0.7	0.8
PMutation	0.3	0.4	0.5
mu	0.01	0.02	0.03
sigma	0.07	0.1	0.2

5 Solution methods

Due to the computational complexity of the model to solve medium- to large-sized problems using an exact solution, two multi-objective meta-heuristic algorithms (i.e., NSGA-II and MOVDO) are developed. The proposed algorithms are used to obtain near-optimal solutions.

5.1 Non-dominated sorting genetic algorithm (NSGA-II)

A genetic algorithm (GA) is an optimization search methodology that follows the natural evolution principles. Taking its inspiration from the process of genetic evolution, this algorithm starts with an initial population of chromosomes that are defined as strings, containing proposed values of variables that lead to possible solutions. To evaluate these chromosomes, the fitness function is defined. As a part of the GA's evolution process, superior chromosomes (i.e., chromosomes with higher fitness values) are selected as parents from which the new chromosomes with their combined characteristics are generated.

To solve the proposed two-stage multi-objective model, the following steps are used to develop a new GA-based solution methodology (NSGA-II): (1) Generate an initial population, (2) Calculate the fitness values, (3) Non-dominated sorting of solutions and calculate the crowding distance, (4) Implement crossover and mutation to generate new chromosomes, (5) Integration of the initial and newly generated chromosomes from the crossover and mutation operators, (6) Replace the parent chromosome with the best-integrated chromosomes from Step 5, and (7) Repeat Steps 1 to 6 until a pre-defined generation number or the satisfaction of a termination condition is reached.

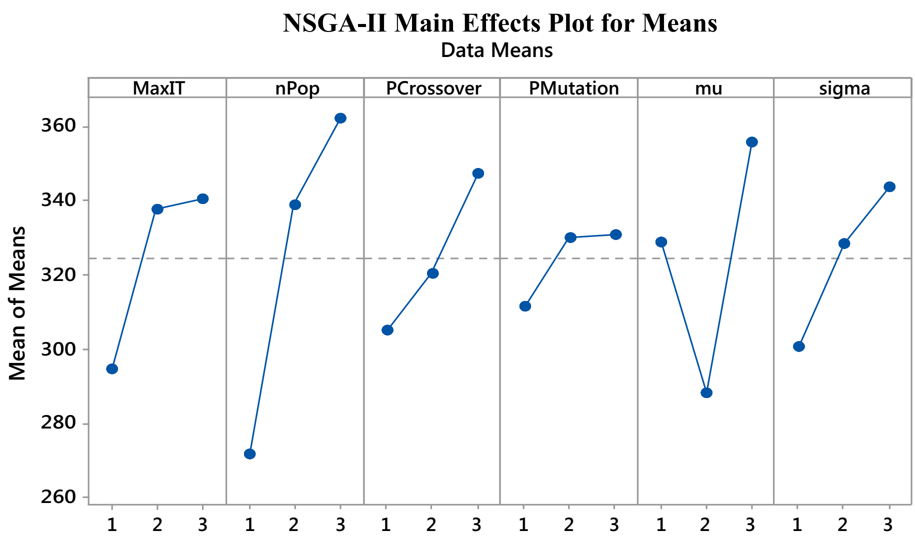


Fig. 2 Mean of deviation for parameter levels of NSGA-II

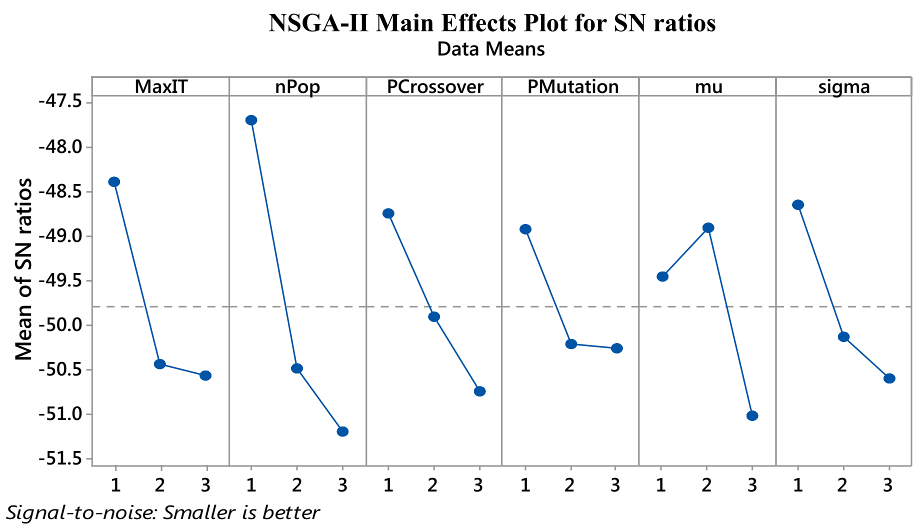


Fig. 3 Signal to noise (S/N) ratio for the parameter levels of the NSGA-II

The parameters for the proposed NSGA-II are presented in Table 2. The different levels of each parameter considered in the NSGA-II are considered using the Taguchi method and are shown in Table 3.

The Taguchi method tends to solve a problem by using a specific number of executions determined in the first step. Next, the performance measures of the multi-objective algorithm are determined, regardless of their scale, by using relative percentage deviation (RPD). The total weights are used as the input in Minitab software, using which the

Table 4 Optimal levels for the NSGA-II parameters using the Taguchi method

Parameter	Optimal level
MaxIT	100
nPop	150
PCrossover	0.6
PMutation	0.3
Mu	0.02
Sigma	0.07

levels of the algorithm's parameters are optimized. Figures 2 and 3 depict the computational results of the Taguchi method. The optimal levels for each parameter of the NSGA-II obtained are provided in Table 4.

5.2 Multi-objective vibration damping optimization (MOVDO)

Vibration damping optimization (VDO) is originated from the vibration damping theory and developed by Mehdizadeh and Tavakkoli-Moghaddam (2008). There is a relationship between the behavior of a damping vibrator system and the combinatorial optimization in finding the minimum value function considering multiple parameters (Mehdizadeh et al. 2015). The vibration gradually decreases as the energy source of a vibrator is cut off. Hence, the vibrator eventually drops out and changes to a damping mode. Using the same concept, Hajipour et al. (2014) developed a multi-objective version of the VDO algorithm (MOVDO) to tackle the more complex multi-objective optimization problems. In this paper, we considered the fast non-dominated sorting (FNDS) and crowding distance (CD) concepts to develop a new MOVDO algorithm to solve the proposed two-stage model for humanitarian logistics and emergency response. The four steps involved in solving an optimization problem using the VDO algorithm include (1) Problem coding; (2) Defining fitness function; (3) Defining the generation of a neighbor solution mechanism; and (4) Defining vibration damping conception.

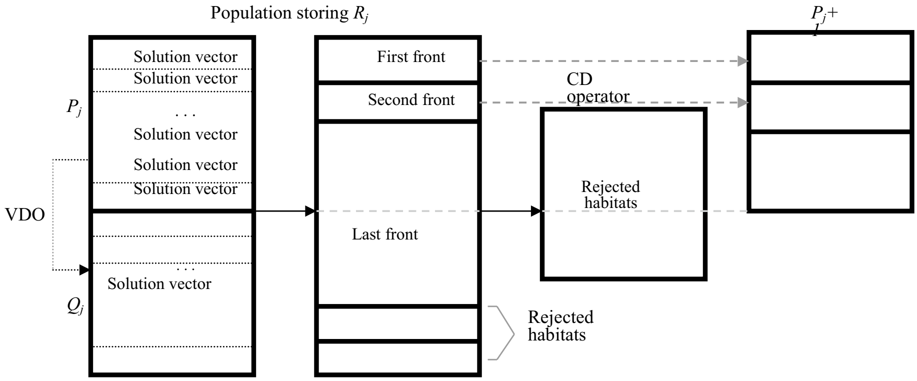


Fig. 4 Evolution process in the proposed MOVDO algorithm

Table 5 Evaluating the MODVO parameters in three different levels

Parameters	Low level (1)	Medium level (2)	High level (3)
MaxIt	60	80	100
nPop	50	70	100
A_0	4	6	8
L	3	5	7

Table 6 Experiments by the Taguchi method for the parameter setting of the MOVDO algorithm

Experiment no.	*MaxIt*	*nPop*	$\boldsymbol{A}_0$	L
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	1	2	2	2
5	1	2	2	2
6	1	2	2	2
7	1	3	3	3
8	1	3	3	3
9	1	3	3	3
10	2	1	2	3
11	2	1	2	3
12	2	1	2	3
13	2	2	3	1
14	2	2	3	1
15	2	2	3	1
16	2	3	1	2
17	2	3	1	2
18	2	3	1	2
19	3	1	3	2
20	3	1	3	2
21	3	1	3	2
22	3	2	1	3
23	3	2	1	3
24	3	2	1	3
25	3	3	2	1
26	3	3	2	1
27	3	3	2	1

Figure 4 shows the process of determining all non-dominated first-layer chromosomes. The initial population of R is compared and sorted. The multi-objective mathematical model is solved for the first layer of non-dominated chromosomes. To determine the second layer of non-dominated chromosomes, the selected solutions of the former chromosomes are temporarily ignored. This procedure continues until all chromosomes are placed in layers $k = 1, 2, \ldots, M$. f_k represents the number of non-dominated solutions in pure layers after population sorting, and the CD parameter is the value of layers according to the relative crowding of each solution.

Table 7 Summary of Iran's severe earthquake statistics in the last century

No	Magnitude (Richter)	Casualties and Damage	Location	Year
1	7.4	8,000 deaths; destruction of 46 villages	Garmab (Baghan)	1907
2	6.5	381 deaths; destruction of 200 villages	Eshgh Abad	1948
3	6.7	191 deaths; destruction of 110 villages	Nahavand	1958
4	6.1	4,000 deaths; destruction of 57% of town	Lar	1960
5	7.2	11,000 deaths	Buein Zahra	1962
6	7.3	10,005 deaths; destruction of 16 villages	Dasht Biaz Khorasan	1968
7	7	600 deaths; destruction of 563 villages	Bandar Abbas	1974
8	7.7	91,006 deaths; destruction of 61 villages	Tabas	1978
9	7.1	850 deaths; destruction of 150 villages	Ghaenat	1979
10	6.7	8201 deaths; destruction of several villages	Kerman (Jalbaf)	1981
11	7.3	3100 deaths; destruction of several villages	Kerman (Sirjan)	1981
12	7.4	50,000 deaths; destruction of 40% of the town	Rudbar-Manjil	1990
13	6.3	530 deaths; destruction of 20 villages	Buein Zahra	2001
14	6.6	33,000 deaths; destruction of 90% of the town	Kerman (Bam)	2003
15	4.6	612 deaths; destruction of 10 villages	Zarand	2004
16	3.6	Landslides; severe damage	Firouz Abad	2004
17	6.1	70 deaths	Borujerd	2006
18	3.6	84 deaths; 1246 injuries	Dorud and Lorestan	2006
19	4.9	100 injures	Dorud	2010
20	6.2	250 deaths; more than 2000 injuries	Ahad and Zarghan	2011
21	7.8	1000 deaths	Saravan	2013
22	7.3	630 dead; 8100 injuries	Kermanshah	2017

Two algorithms used in the solution methodology do have some functional differences, however, there are also some similarities. The neighboring scheme in the MODVO algorithm is similar to the mutation scheme in the NSGA-II. An evaluation function is an objective function and the termination condition is the same as the NSGA-II. The maximum iteration number ($MaxIt$), initial population ($nPop$), initial domain (A_0) and the maximum iteration number for each domain (L) are computed according to the Taguchi method. For the computational experiments in this paper, three levels are considered as low, medium, and high. The three levels considered for each parameter and the parameter setting of the MOVDO algorithm are shown in Tables 5 and 6.

6 Case study on humanitarian logistics in the city of Tehran

To illustrate the application of the proposed model, the case of disaster preparation and response in the city of Tehran, Iran is considered. Iran is one of the 10 earthquake zones in the world with 96% of its land is located on the faults. In the last century, Iran is ranked as the fourth country in the global earthquake statistics with 89 earthquakes and almost 130 thousand casualties. Table 7 summarizes the severe earthquakes that occurred in Iran during the last century and the respective casualties and damages (Akbari et al. 2004).

Fig. 5 Location of District 3 in Tehran

The Bam earthquake was one of Iran's most disastrous earthquakes that occurred on the 26th December 2003 (5:26:26 AM) and measured 6.6 on the Richter scale (Movahedi, 2005). This devastating earthquake killed around 33,000 people and resulted in almost the same number of casualties (Ghafory-Ashtiany & Hosseini, 2008). 80 percent of buildings were completely destroyed by the earthquake, which included hospitals, firefighting centers, telecommunication centers, water supply, power utilities, and even relief centers. The perceived humanitarian logistics during the first 40 h of a disaster were reported to be highly unsatisfactory due to inefficient relief planning and response, such as the discrepancy in guiding aid vehicles (Wassenhove, 2006). Relief vehicles reportedly blocked the roads right at the entrance of the town, consequently disrupting public assistance until the following day. Moreover, proper aid services were not provided to the rescued people due to the lack of proactive emergency planning by voluntary and government agencies. The inadequate stock of necessary items and the delay in disaster response, such as providing tents to the area and establishment of local camps in remote regions were only some of the critical issues reported by the public and officials (Movahedi, 2005).

The city of Tehran, which is also the capital of Iran, includes 22 different districts. Since Iran is located in the earthquake zone, the city of Tehran must plan efficiently for humanitarian logistics and emergency response. For this case problem, only District 3 is considered. There are three critical areas, namely Vanak, Ararat, and Davoodieh located in District 3 (see Fig. 5). The proposed two-stage multi-objective model is used to solve the real case of the city of Tehran and conduct computational experiments. The real data extracted from GIS software is used for this case.

To locate the emergency shelters, it is proposed that the geographic area of the city is first divided into multiple sites. Each site is investigated for its suitability for the emergency shelter construction in the pre-disaster phase. The candidate emergency shelter sites are then selected based on logistics accessibility criteria (e.g., access to roads and facilities) and the natural conditions (e.g., gradients and soil type). In the pre-disaster emergency shelter selection process, the priority is given to (1) public parks and gardens, (2) schools and higher education centers, (3) cultural places, art centers, and museums, (4) outdoor and covered parking areas, and (5) mosques, churches, and sacred places.

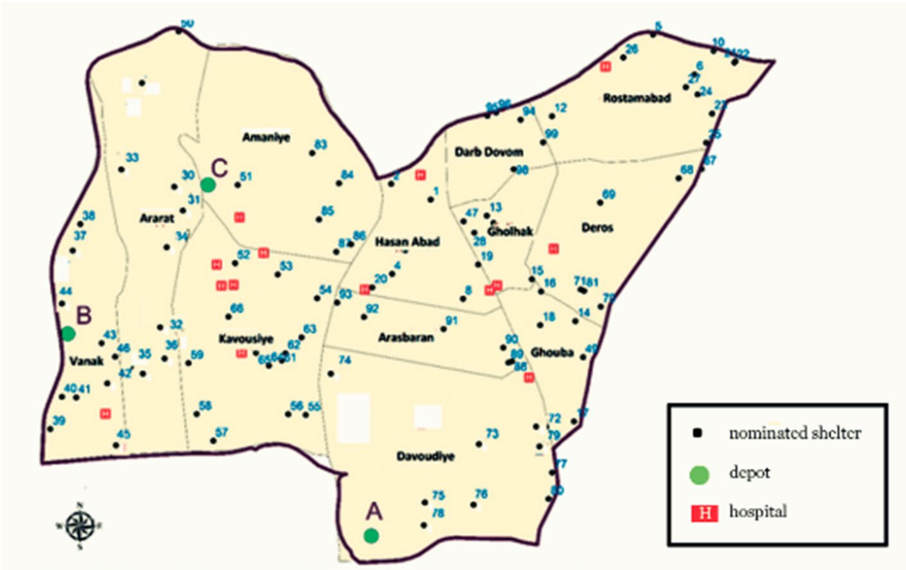


Fig. 6 Nominated sites and current hospitals in District 3 of Tehran

The maximum number of shelters in three critical areas is set 18 by the city council of District 3. Also, the maximum and minimum depots that can be assigned to each shelter are determined as 1 and 2, respectively. Figure 6 depicts the nominated sites for establishing the shelter, selected depots, and the current location of hospitals in District 3.

In the case study, two types of vehicles are considered for the evacuation of people having the capacities of 40 non-admitted patients and 2 admitted patients (needs hospitalization) respectively. For the distribution of relief supplies, the number of vehicles at each depot is considered to be 5. The upper bound for the total number of temporary depots is 3 and the weighted coefficients of depots are 0.2, 0.3, and 0.5, respectively.

Moreover, the cost of a laid-off vehicle in a depot is 5. The number of routes between each shelter and each critical area and the number of routes between each shelter and each depot are randomly selected from the set of $\{1, 2, 3\}$ with the equal probability of 1/3. Also, the distance between critical areas and shelters through each route is considered to be known. The traveling cost from each depot to each shelter for every route follows a uniform distribution [7, 14]. The required time for vehicles traveling from depots to the shelter is also uniformly distributed within [1, 10]. The maximum allowed distance from the shelters to the hospitals and from the shelters to the main road is 3000 and 2000 respectively, and the maximum allowed mileage for evacuating people from the critical areas is 2000.

The weighted coefficients for dissatisfaction with the allowed delay, disallowed delay, traveling from depots to shelters and distributive injustice are assumed to be 0.1, 0.2, 0.1, and 0.4, respectively. It is often observed that in the time of crisis, people may show intense and irreparable reactions if they find themselves as victims of discrimination and distributive injustice when comparing the quality of aid and assistance delivery. For example, they may leave the place before receiving any relief and assistance causing irreparable effects. Therefore, it is necessary to consider the dissatisfaction and distributive injustice cost as the most important factor in having the highest weight. The minimum and maximum percentage allowed of people for opening shelters are set as

Table 8 Number of injuries, deaths, and vehicles in three studied areas in District 3

Critical areas	District population	Number of displacements	Probability of being a healthy and non-admitted person	Number of non-admitted patients	Number of deaths	Number of injured patients needed hospitalization	Number of vehicles
Davoodieh	27,115	18,836	0.99	869	78	197	562
Vanak	18,930	13,513	0.982	882	84	240	452
Ararat	17,156	11,742	0.988	493	43	141	362

Table 9 Weight and capacity of nominated sites and their distance to depots and the main road

Critical area	Nominated site no	Nominated site weight	Nominated site capacity	Distance to depot A	Distance to depot B	Distance to depot C	Distance to the main road
Davoodieh	30	0.45	1500	337.3676	318.4538	91.42075	817
	31	0.46	1000	185.8049	194.4073	142.5553	890
	32	0.5	3000	171.2346	166.3671	259.0939	879
	33	0.45	4475	485.337	352.9551	171.5404	1279
	34	0.42	3010	303.4746	257.2514	39.67713	1385
	35	0.35	1945	234.042	111.4172	162.78	1094
	36	0.49	3500	213.1602	111.2391	185.3664	946
	37	0.47	10,000	377.6399	95.23193	161.1882	1148
	38	0.38	10,000	379.4472	124.38	144.4533	780
	39	0.37	10,000	335.599	106.6768	328.1682	1225
	40	0.32	10,000	329.3086	73.30128	288.3827	1013
Vanak	41	0.51	10,000	300.7356	74.34848	278.1124	1071
	42	0.5	10,000	266.2445	70.5434	240.8382	1488
	43	0.52	10,000	293.002	39.21079	218.9917	1005
	44	0.49	10,000	355.1629	31.55224	214.2441	1313
	45	0.46	5000	50.02558	271.5009	276.1422	776
	46	0.61	4500	78.84695	265.0635	268.0087	742
	72	0.48	5000	218.445	349.8032	266.0572	1007
	73	0.46	4000	142.0573	372.7481	316.9591	851
	74	0.55	3000	353.9006	313.1807	352.2625	1368
	75	0.39	2000	113.2273	349.4409	331.7259	1357
Ararat	76	0.4	10,000	158.4518	388.6148	358.0522	805
	77	0.2	3000	158.4518	388.6148	358.0522	1100
	78	0.53	5000	199.124	392.4713	294.1857	1188
	79	0.45	3000	196.1928	392.0916	285.0053	790
	80	0.6	4000	197.4683	387.0341	273.3017	1370

50 and 100 percent of the total capacity, respectively. The 8-h proposed time period considers 3 h of for the relief supplies delivery from the depots to the shelters without any delay, 2 h of delivery with permissible delivery, and 3 h of impermissible delay for the relief supplies such as water, tent, food, etc. Table 8 provides information related to population, death, and injury numbers.

According to the above information, the patients are mainly divided into admitted and non-admitted patients. In this study, the number of injuries is defined by the admitted patients only and the number of deaths is not considered. Also, the ambulance is used for evacuating injured people from the critical areas to the shelters and the number of displaced people is equal to the demand of critical areas for evacuation. Table 9 shows the weight and capacity of the nominated sites for emergency shelters and their distance from the depots (i.e. A, B, and C) as well as the main road. The weights for nominated sites are obtained based on three criteria, namely the land slope, soil type, access to the main road, and urban facilities.

Table 10 presents the volume and load weight, the penalty cost for the delayed delivery of goods, and the amount of initial inventory at each depot. Also, the maximum load capacity of each truck is 100,000 weight units and the maximum load volume of each truck is 264 units. All this data is taken as an input in solving the case problem. Since the problem involves a large data set, it is solved using two heuristics for multi-objective optimization and the results are discussed in the next section.

7 Computational study

In this section, the results obtained for the humanitarian location-allocation problems, identified in the case study, are examined. The considered problems range from small- to large-sized problems. The GAMS and CPLEX 11 software are used on an Intel(R) CoreTM2.50 GHz Personal Computer with 4 GB RAM for running the computational experiments. Matlab software is used to code and run both the NSGA-II and MOVDO heuristics. The computational results are compared based on five standard criteria, i.e. mean ideal distance (MID), spacing, diversity, NOS, and time (see Table 11).

After comparing the computational results, the five criteria are converted into a response factor to generate output from each experiment. The S/N ratio is calculated for the obtained response factor (see Fig. 7). The optimal level of parameters is determined using MATLAB and is presented in Fig. 8.

Tables 12 and 13 summarize the optimal levels of S/N ratio parameters for both NSGA-II and MOVDO.

To examine and compare the performance of the developed algorithms (representation scheme and neighborhood structure), 10 problem instances with different sizes (including our case-study problem) are solved using NSGA-II, MOVDO, and ε-constraint methods. The characteristics of all problem instances are shown in Table 14 and their computational results are summarized in Table 15. It can be seen from Table 15 that the quality of the solution drops as the size of the problem instance increases. In the ε-constraint method, the computational time increases exponentially on increasing the problem size. On the other hand, the NSGA-II and MOVDO algorithms perform well for small-sized problems, also their computational times do not increase exponentially for larger problems. It can be also observed from Table 15 that the NSGA-II is superior to the MOVDO in some criteria, but the MOVDO running time is less than that of the NSGA-II.

Table 10 Volume and weight of each commodity, penalty cost for delivery delay of goods, and initial inventory

Commodity	Weight	Volume	Penalty cost of goods delivery to shelters with allowed delay	Penalty cost of goods delivery to shelters with disallowed delay	Current inventory in depot A	Current inventory in depot B	Current inventory in depot C
Type 1	9.2	0.2	10	20	4050	1800	4050
Type 2	2.7	0.45	10	20	4050	1800	4050
Type 3	2.5	0.16	10	20	4050	1800	4050
Type 4	10	0.2	10	20	4050	1800	4050

Pareto-Front solutions of all three methods are determined using actual inputs. When comparing the solutions on the factor Mean ideal distance (MID), the ε-constraint method seems to be superior to the NSGA-II and MOVDO algorithms (Table 15); however, the difference in the performance between the ε-constraint method and the algorithms is not statistically significant. Therefore, it is found that almost all three algorithms perform efficiently according to this criterion. However, for the problem instances of larger size, where the ε-constraint method takes high computational time, two developed algorithms can be efficiently used to find near-optimal solutions. It is also observed that the performance of NSGA-II is better than the MOVDO on the computational time criterion.

The performance of the proposed algorithms is superior to the ε-constraint method for diversity criterion in some of the instances. It is also observed that as the value of this criterion increases, the performance of algorithms improves. For larger problem sizes, the value of this criterion increases, and the ε-constraint method shows superiority. Also, the performance of NSGA-II is slightly superior to the MOVDO.

Table 11 Computational results of the NSGA-II and MOVDO for the large-sized problems

No.	NSGA-II					MOVDO				
	MID	Spacing	Diversity	NOS	Time (s)	MID	Spacing	Diversity	NOS	Time (s)
1	27.1	1.4	5.6	12.0	15.8	42.5	3.8	6.7	3.0	5.6
2	29.1	2.2	3.3	18.0	14.1	45.3	1.1	10.6	14.0	5.2
3	28.7	1.7	4.4	11.0	13.2	36.2	1.3	10.4	11.0	6.5
4	26.6	0.9	4.9	15.0	64.5	36.2	2.2	6.9	6.0	25.2
5	26.5	0.5	4.5	9.0	67.4	37.7	3.5	4.0	10.0	21.8
6	26.4	2.3	4.7	11.0	57.1	41.4	2.5	12.8	14.0	21.9
7	26.7	1.8	3.1	5.0	90.7	37.6	2.5	11.6	3.0	32.4
8	26.4	0.2	2.8	13.0	86.1	31.9	2.2	6.6	13.0	31.5
9	26.9	0.9	5.6	7.0	88.5	42.4	2.6	5.7	15.0	31.2
10	26.7	1.0	3.1	9.0	29.3	32.5	1.7	6.1	7.0	10.5
11	31.3	0.2	4.1	20.0	28.0	33.8	3.6	11.3	5.0	10.5
12	26.5	2.3	4.3	15.0	28.9	33.3	2.4	8.9	5.0	10.9
13	27.5	1.4	3.8	20.0	97.0	44.4	3.9	9.5	12.0	42.3
14	26.3	1.7	4.1	7.0	100.4	41.2	2.7	14.9	13.0	42.9
15	27.0	2.7	4.2	19.0	105.1	35.6	3.1	3.2	11.0	45.5
16	26.8	0.5	5.3	16.0	144.3	37.5	2.7	11.9	5.0	68.1
17	26.0	1.7	2.7	18.0	138.8	36.9	2.1	10.3	8.0	66.9
18	26.1	1.3	4.8	13.0	139.8	36.6	2.3	8.8	3.0	67.5
19	28.4	1.9	2.4	11.0	39.5	32.0	3.0	5.8	9.0	15.5
20	26.1	1.6	3.6	18.0	41.4	31.8	3.5	10.4	9.0	15.4
21	26.5	2.0	5.0	18.0	41.6	32.2	2.5	11.1	9.0	17.7
22	26.0	0.0	4.6	17.0	148.0	33.6	3.5	12.5	9.0	56.1
23	26.9	0.2	2.6	11.0	150.3	33.3	3.7	10.6	12.0	57.2
24	25.9	2.3	2.1	13.0	148.0	30.1	2.1	14.2	10.0	55.2
25	25.6	2.2	2.6	18.0	191.6	35.2	1.8	6.5	4.0	79.5
26	26.6	1.8	4.9	18.0	192.0	33.3	3.6	9.4	11.0	78.0
27	26.2	0.2	3.3	8.0	191.2	39.9	1.4	11.8	6.0	76.9

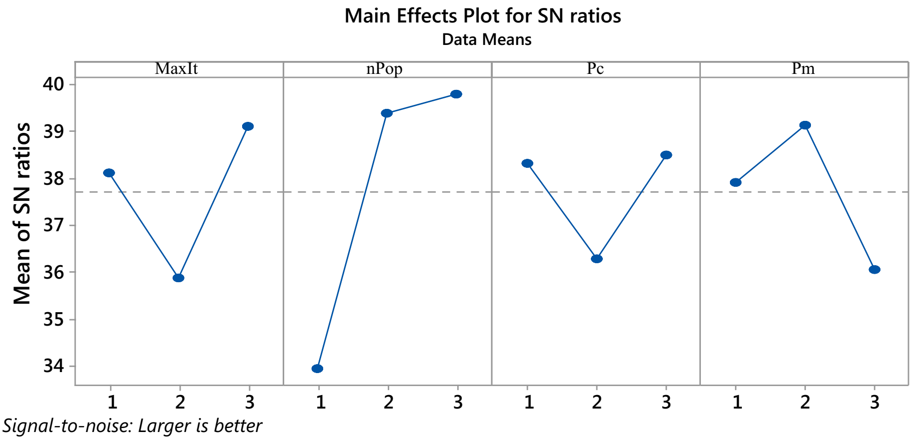


Fig. 7 S/N ratio for the parameter setting using the Taguchi method for the NSGA-II

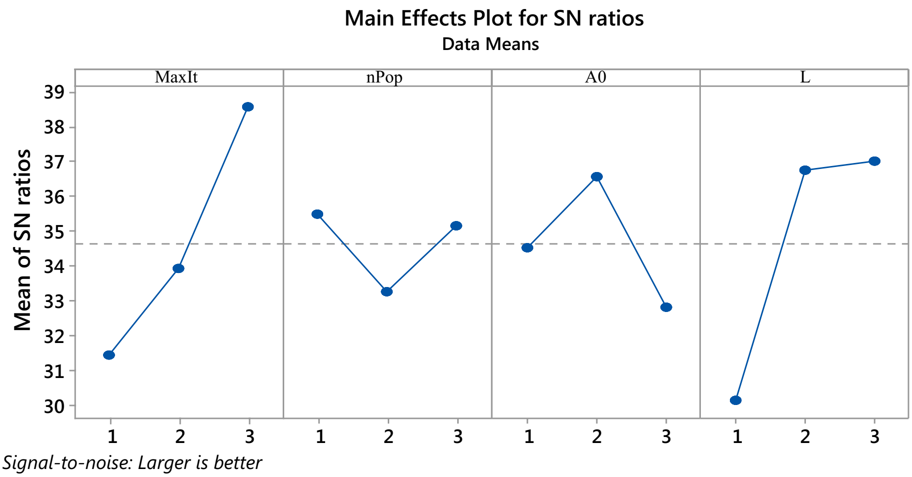


Fig. 8 MINITAB output for the parameter setting

Table 12 Optimal levels for the NSGA-II

	MaxIt	nPop	Pc	Pm
NSGA-II	Level 3	Level 3	Level 3	Level 2
	150	150	0.8	0.3

The objective function values of these algorithms for the problem instances including the case study are presented in Table 16. This table shows the high-quality Pareto-Front solutions that are obtained via the NSGA-II (see Fig. 9). The running time of the NSGA-II is also found to be significantly less than GAMS software.

The results from these numerical experiments show that solution gaps among NSGA-II and MOVDO, and ε-constraint methods are less than 7%. However, considering the

Table 13 Optimal levels for the MOVDO

	MaxIt	nPop	A_0	L
MOVDO	Level 3	Level 2	Level 2	Level 3
	150	100	6	7

Table 14 Characteristics of the random instances

No	I	J	M	P	K	H
1	20	2	2	2	2	10
2	25	3	2	2	2	12
3	30	3	3	3	3	14
4	35	4	3	3	3	16
5	40	4	4	4	4	18
6	45	4	4	4	5	20
7	50	5	5	5	6	22
8	55	5	5	6	7	24
9	60	6	5	6	8	26
Real case	26	3	2	3	2	14

first and second level solutions simultaneously, Problem instance 2 and 3 obtains the best solutions of the NSGA-II and MOVDO methods, which have the third-lowest objective values in addition to being in the Pareto-front solution. Table 16 also shows that while all algorithms generate diverse solutions, the proposed meta-heuristic algorithms perform almost the same as the ε-constraint method. As a result, 10 Pareto solutions are obtained with an appropriate dispersion and expansion in the solution space.

The case study discussed in Sect. 6 is also solved using the same approach. The location-allocation problem is solved using 26 nominated sites and18 sites are optimally selected for shelter establishment (see Fig. 10). It is shown using Fig. 10 that the nominated sites in Ararat (30, 31, 32, 33, 34, 35, and 36), Vanke (37, 42, 44 and 45), and Davoodieh (72, 73, 74, 75, 76, 78 and 79) meet the requirements to be selected as optimal shelters. The demand in the critical areas can be fully covered using the capacity of selected shelters. Also, the number of selected shelters does not exceed its upper bound, and all three resources A, B, and C are active. It can also be seen that people are assigned to the established shelters and three critical areas are well covered.

The number of existing vehicles in routes for evacuation from the critical areas to shelters, the percentage of transporting people, and depot allocation are illustrated in Table 17. As observed in this table that the demand for critical areas is covered and the number of vehicles on routes is not higher than the number of vehicles in critical areas.

The problem solution ensures that the percentage of people allocated to the shelters does not exceed the shelter capacity and the demand for the evacuation of critical areas is covered. The problem size is large and contains a high volume of outputs related to goods allocating to depots. Therefore, Table 18 only shows the delivered goods from depot A to shelter 79 in the Ararat district.

A detailed sensitivity analysis is also conducted to examine the behavior of objective functions by changing the key parameters. The impact of the change in shelter capacity, demand in the critical area, and shelter distances to the critical area are studied. The impact of demand uncertainty on the objective functions is also investigated. The change in the

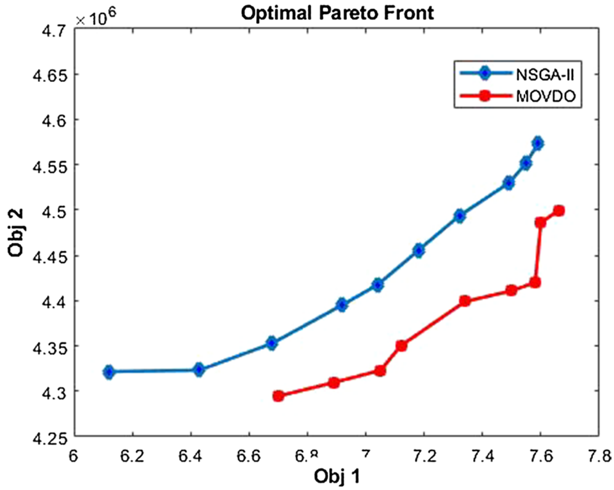
Table 15 Computational results for solving 10 instances using the NSGA-II, MOVDO, and ε-constraint methods

Test no	NSGA-II					MOVDO					ε-constraint				
	MID	Spacing	Diversity	NOS	Time (s)	MID	Spacing	Diversity	NOS	Time (s)	MID	Spacing	Diversity	NOS	Time (s)
1	775.21	2.43	62.9	11	69	839.8	2.3	58.3	10	49	682.9	5.98	25.3459	4	26
2	709.7	11.22	70.69	10	91	774.7	10.7	69.8	12	57	555.9	17.06	120.87	13	30
3	908.05	6.54	144.33	10	115	927.5	6.0	139.3	7	78	712.9	22.39	162.22	8	120
4	1500	10.33	165.43	13	117	1638.3	9.5	163.1	13	88	1262.5	5.86	137.77	30	320
5	1621	5.56	165.38	12	127	1729.5	5.4	162.3	12	86	1303.1	7.85	254.83	18	644
6	1864	6.0	158.50	6	137	1899.0	5.7	145.2	8	96	1645.8	10.2	224.18	19	1030
7	2341	7.83	126.38	12	170	2423.1	7.4	117.2	12	116	1988.3	10.78	258.93	19	1280
8	3420	12.98	220.45	7	253	3748.9	12.0	199.4	9	155	–	–	–	–	–
9	3784	15.67	289.23	15	299	4150.4	14.4	285.4	16	193	–	–	–	–	–
Real Case	2554	10.30	183.45	7	101	2705.2	9.6	176.4	8	65	2017.8	7.85	195.66	16	37

Table 16 Objective values by different solution algorithms

	ε-constraint			NSGA-II			MOVDO		
	First stage		Second stage	First stage		Second stage	First stage		Second stage
	OV1	OV2	OV3	OV1	OV2	OV3	OV1	OV2	OV3
1	7.86	4,486,326	3,191,529	7.59	4,573,764	3,865,216	7.66	4,499,348	3,785,932
2	7.84	4,448,800	3,640,098	7.55	4,551,856	3,173,412	7.60	4,485,940	3,140,394
3	7.81	4,411,290	3,564,322	7.49	4,529,759	3,325,736	7.58	4,420,110	3,102,019
4	7.79	4,373,764	3,625,850	7.32	4,493,288	3,919,164	7.50	4,410,920	3,883,102
5	7.69	4,351,856	3,625,096	7.18	4,455,403	3,300,348	7.34	4,399,039	3,245,956
6	7.59	4,309,759	5,141,542	7.04	4,417,502	3,792,227	7.12	4,350,172	3,710,928
7	7.49	4,280,320	4,254,638	6.92	4,395,375	3,849,349	7.05	4,322,930	3,780,394
8	7.09	4,278,751	4,809,316	6.68	4,352,857	4,255,545	6.89	4,309,472	4,167,930
9	–	–	–	6.43	4,323,123	3,255,921	6.70	4,294,302	3,202,182
10	–	–	–	6.12	4,321,539	4,741,078			

Fig. 9 Pareto front obtained via the NSGA-II



objective functions considering different levels of uncertainty are also studied. The findings are discussed below:

- *Impact of the shelter capacity reduction*

  The impact of shelter capacity on the objective function values is shown in Fig. 11. It can be observed from this figure that the first and second objective values decrease by reducing the shelter capacity. It is observed that the reduction in shelter capacity also affects the percentage of people allocated to the shelters and the constraints for minimizing the shelter exploit. Therefore, the obtained results are justified. The third objective value linearly decreases by reducing the shelter capacity, which means as the shelter capacity decreases, the number of people in the shelter will reduce which further reduces the demand for relief supplies. Therefore, the number of vehicles used for

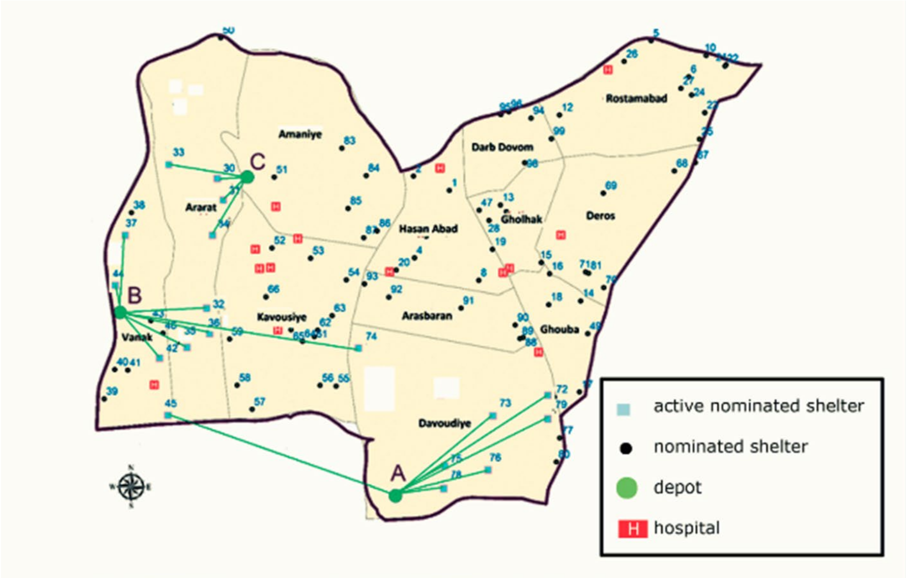


Fig. 10 Active nominated sites for shelter establishment in District 3

distribution from depots to shelters declines, and dissatisfaction costs on the delayed delivery of relief supplies and distributive injustice costs also decrease.

- *Impact of reduction in the critical areas' demand*

  It can be seen from Fig. 11 that the values of the second objective function decreases as the critical areas' demand is reduced. This is due to a reduction in the overall distance required to travel from the critical areas to the shelters as a result of the reduction in demand for the evacuation. Considering the interdependency between the critical areas' demand and shelter capacity, the decrease in each factor proportionally reflects onto the second objective function. Additionally, the reduction in the demand for the critical areas for evacuation also reduces the number of people needing relief supplies and, consequently, reduces the injustice costs and the dissatisfaction caused by the delayed delivery or the lack of delivery. The number of trips also declines and, as a result, the value of the third objective function also decreases.
- *Impact of a decrease in the distance between the shelters and critical areas*

  It can be observed from Fig. 11 that as the distance between the shelters and critical areas decreases, the value of the second objective function also decreases. The number of relief supplies to be distributed from the depots to the emergency shelters depend on the number of rescued people. This also tends to impact the shelter population, depot capacity, and volume and weight capacity of trucks. The cost of injustice and dissatisfaction is also a function of the volume and the time of delivered relief supplies.
- *Impact of demand uncertainty on the case study problem*

To study the impact of demand uncertainty during the integrated humanitarian logistics and emergency response problem, different levels of uncertainty are considered in the case problem. Three levels of demand uncertainty at 0.25, 0.5, and 0.75 are considered and the model is solved for each scenario. The objective function values obtained at different

Table 17 Some information in three critical areas in Discrete 3

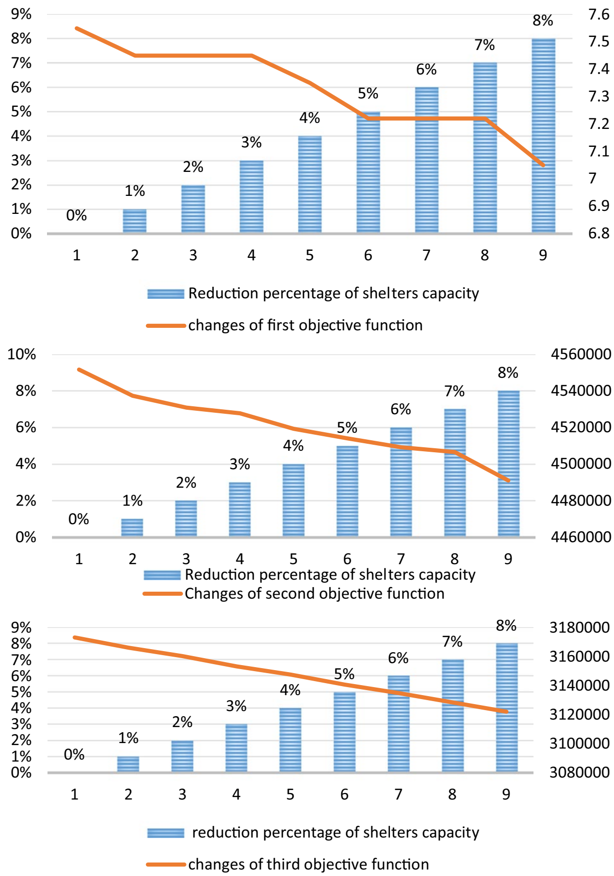
Critical areas	Nominated site no	Vehicles in route 1	Vehicles in route 2	Transported people from route 1 (%)	Transported people from route 2 (%)	Covering depot
Davoodieh	30	0	39	0	0.106	C
	31	0	8	0	0.022	C
	32	0	61	0	0.169	B
	33	0	84	0	0.233	C
	34	55	0	0.153	0	C
	35	0	46	0	0.125	B
	36	69	0	0.191	0	B
	37	184	0	0.406	0	B
	38	0	0	–	–	–
	39	0	0	–	–	–
	40	0	0	–	–	–
Vanak	41	0	0	–	–	–
	42	0	84	0	0.185	B
	43	0	0	–	–	–
	44	0	85	0	0.187	B
	45	0	101	0	0.222	A
	46	0	0	–	–	–
	72	0	89	0	0.159	A
	73	75	0	0.133	0	A
	74	0	59	0	0.105	B
	75	0	26	0	0.046	A
Ararat	76	0	164	0	0.292	A
	77	0	0	–	–	–
	78	0	89	0	0.159	A
	79	0	60	0	0.106	A
	80	0	0	–	–	–

levels of demand uncertainty is presented in Fig. 12. According to this figure, by increasing the uncertainty level, the value of the first objective function decreases. This means that as demand fluctuates are more, a higher number of depots and shelters are required. Therefore, the value of the first objective declines. It is also observed that higher is the demand uncertainty, there is a need to transfer a higher amount of essential goods leading to high transportation activity and traversed distance. As a result, the values for the second and third objective function increases. To cater to the uncertain demand, the model tends to distribute more relief supplies, which results in increased cost of network distribution. The proposed model attempts to fulfill the uncertain demand by deviating from the optimal solution. The more uncertainty in the demand will result in more deviation from the optimal solution.

Table 18 Proposed output plan for goods allocation

Delivered goods											
Type 1			Type 2			Type 3			Type 4		
Route no	Period	Goods quantity	Route no	Period	Goods quantity	Route no	Period	Goods quantity	Route no	Period	Goods quantity
1	1	2000	1	1	2000	1	1	50,620	1	1	2000
1	2	2000	1	2	2000	1	2	50,620	1	2	2000
1	3	2000	1	3	2000	1	3	50,620	1	3	2000
1	4	2000	1	4	2000	1	4	2000	1	4	2000
2	5	2000	2	5	2000	2	5	2000	2	5	2000
1	6	2000	1	6	2000	1	6	2000	1	6	2000
1	7	2000	1	7	2000	1	7	2000	1	7	2000
1	8	2000	1	8	2000	1	8	2000	1	8	2000

Fig. 11 Changes in the objective values by reducing the shelter capacity



8 Managerial and theoretical implications

Managerial implications and theoretical contributions from this study are discussed below:

8.1 Managerial implications

This study can bridge the gap between disaster planning and disaster response stages by integrating the prepositioning of emergency shelters and depots and distribution of relief supplies in coordination with the evacuation activities. The proposed model can help the policymakers to optimally identify and locate the emergency shelters and depots with appropriate capacities during the preparation phase of disaster planning. Focusing on minimizing the dissatisfaction and distributive injustice costs, this study can aid disaster relief agencies and government bodies to better coordinate the evacuation and distribution of relief supplies during the disaster response phase by optimally allocating their resources and optimizing the routes within a given time window. Overlooking the uncertainty of demand may lead to high dissatisfaction, injustice, cost, and can also lead to casualties. This study can help decision-makers to incorporate demand uncertainty in humanitarian logistics operations. The real-life disaster scenario is a large-scale problem that may take

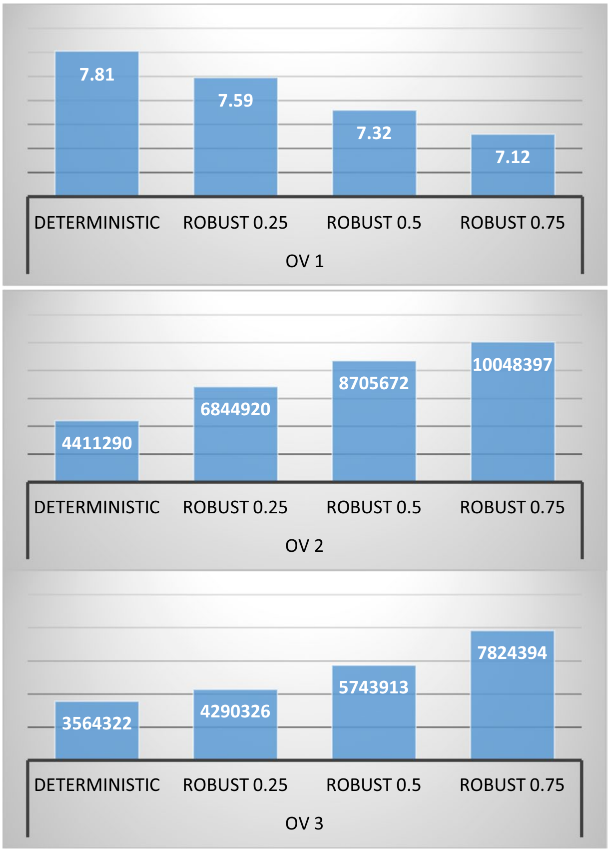


Fig. 12 Impact of different uncertainty levels on the objective function values

a high computation time. The proposed solution methods can assist decision-makers in obtaining a near-optimal solution in a reasonable time.

8.2 Theoretical contributions

The paper contributes to the field of humanitarian logistics by proposing a two-stage multi-objective model for integrated disaster preparation and response. The proposed model is a novel attempt to coordinate different disaster relief activities and improve the overall effectiveness of humanitarian logistics operations. The first stage of the model identifies the set of criteria and focuses on the location decisions of emergency shelters and depots. The second stage aims to optimize the evacuation of affected people from the disaster areas and coordinate the distribution of the relief supplies to the rescued people, considering limited vehicle and depot capacity. The proposed model is designed to minimize the distributive injustice and dissatisfaction costs along with other objective functions, ensuring the coordination between various levels of decision making through efficient distribution planning and reduction of delivery delays. The paper also proposed the use of two algorithms namely NSGA-II and MOVDO to obtain near-optimal solutions for large-scale problems. The case of the city of Tehran is studied and solved using the proposed model. The paper also conducts the sensitivity analysis of the model to study the impact of change in certain parameters/resources on the optimal solutions.

9 Conclusion and future work

With frequent occurrences of disaster events, poor management, and lack of coordinated effort by various agencies involved in disaster relief, the need for efficient integrated disaster planning and response has been significantly increased. As a result, planning an effective disaster for the evacuation of people from danger zones to the nearest safe zones and providing them with relief supplies has become the top priority of many government agencies. This paper proposed an integrated two-stage multi-objective mathematical model for disaster preparation and disaster response, considering the real case of an earthquake in the city of Tehran. The first stage of the proposed model evaluates and selects the sites for joint prepositioning of emergency shelters and depots considering a set of criteria to maximize the suitability and minimize the total distance covered between the facilities. The second stage of the model jointly optimizes the evacuation network plan and the distribution of relief supplies such that the total delay time and hence distributive injustice cost is minimized. In this way, the coordination between the evacuation and relief distribution activities is achieved. However, the computational complexity of such integrated models is high and the size of the problem increases. Therefore, to solve the developed integrated model and to present the Pareto-front solutions, two novel meta-heuristic algorithms, namely NSGA-II and MOVDO, were used. Using these meta-heuristics, the optimal depot location and the sites for the shelter establishment were identified. The optimal allocation of the selected shelters to the depots was also identified. Our comprehensive sensitivity analysis of different uncertainty levels revealed that increasing uncertainty magnifies the level of dissatisfaction among the rescued people.

The proposed model can be used in the planning of drinking water reservoirs near the shelters and location of temporary hospitals. Future research directions may include an extension to the presented model by incorporating the post-disaster route disruptions and real-time route adjustments, aiming to minimize the level of dissatisfaction and distributive injustice among the rescued people.

References

Akbari, M. E., Farshad, A. A., & Asadi-Lari, M. (2004). The devastation of Bam: An overview of health issues 1 month after the earthquake. *Public Health, 118*(6), 403–408.

Akgün, İ, Gümüşbuğa, F., & Tansel, B. (2015). Risk based facility location by using fault tree analysis in disaster management. *Omega, 52,* 168–179.

Alem, D., Clark, A., & Moreno, A. (2016). Stochastic network models for logistics planning in disaster relief. *European Journal of Operational Research, 255*(1), 187–206.

Asian, S., & Nie, X. (2014). Coordination in supply chains with uncertain demand and disruption risks: Existence, analysis, and insights. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 44*(9), 1139–1154.

Balcik, B., Beamon, B. M., Krejci, C. C., Muramatsu, K. M., & Ramirez, M. (2010). Coordination in humanitarian relief chains: Practices, challenges and opportunities. *International Journal of Production Economics, 126*(1), 22–34.

Bayram, V., Tansel, B. Ç., & Yaman, H. (2015). Compromising system and user interests in shelter location and evacuation planning. *Transportation Research Part B: Methodological, 72,* 146–163.

Bertsimas, D., & Sim, M. (2004). The price of robustness. *Operations Research, 52*(1), 35–53.
Bish, D. R., Agca, E., & Glick, R. (2014). Decision support for hospital evacuation and emergency response. *Annals of Operations Research, 221*(1), 89–106.
Bozorgi-Amiri, A., Jabalameli, M. S., Alinaghian, M., & Heydari, M. (2012). A modified particle swarm optimization for disaster relief logistics under uncertain environment. *The International Journal of Advanced Manufacturing Technology, 60*(1–4), 357–371.
Campbell, A. M., & Jones, P. C. (2011). Prepositioning supplies in preparation for disasters. *European Journal of Operational Research, 209*(2), 156–165.
Campbell, A. M., Vandenbussche, D., & Hermann, W. (2008). Routing for relief efforts. *Transportation Science, 42*(2), 127–145.
Cavdur, F., Kose-Kucuk, M., & Sebatli, A. (2016). Allocation of temporary disaster response facilities under demand uncertainty: An earthquake case study. *International Journal of Disaster Risk Reduction, 19,* 159–166.
Davis, L. B., Samanlioglu, F., Qu, X., & Root, S. (2013). Inventory planning and coordination in disaster relief efforts. *International Journal of Production Economics, 141*(2), 561–573.
De Vries, H., & Van Wassenhove, L. N. (2020). Do optimization models for humanitarian operations need a paradigm shift? *Production and Operations Management, 29*(1), 55–61.
Dubey, R., Altay, N., & Blome, C. (2019a). Swift trust and commitment: The missing links for humanitarian supply chain coordination? *Annals of Operations Research, 283*(1), 159–177.
Dubey, R., Bryde, D. J., Foropon, C., Graham, G., Giannakis, M., & Mishra, D. B. (2020a). Agility in humanitarian supply chain: an organizational information processing perspective and relational view. *Annals of Operations Research*, Article in Press, 1–21.
Dubey, R., Gunasekaran, A., Bryde, D. J., Dwivedi, Y. K., & Papadopoulos, T. (2020b). Blockchain technology for enhancing swift-trust, collaboration and resilience within a humanitarian supply chain setting. *International Journal of Production Research, 58*(11), 3381–3398.
Dubey, R., Gunasekaran, A., Childe, S. J., Roubaud, D., Wamba, S. F., Giannakis, M., & Foropon, C. (2019b). Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *International Journal of Production Economics, 210,* 120–136.
Duque, P. A. M., Dolinskaya, I. S., & Sörensen, K. (2016). Network repair crew scheduling and routing for emergency relief distribution problem. *European Journal of Operational Research, 248*(1), 272–285.
Erbeyoğlu, G., & Bilge, Ü. (2020). A robust disaster preparedness model for effective and fair disaster response. *European Journal of Operational Research, 280*(2), 479–494.
Faghih-Roohi, S., Ong, Y. S., Asian, S., & Zhang, A. N. (2016). Dynamic conditional value-at-risk model for routing and scheduling of hazardous material transportation networks. *Annals of Operations Research, 247*(2), 715–734.
Falasca, M., & Zobel, C. W. (2011). A two-stage procurement model for humanitarian relief supply chains. *Journal of Humanitarian Logistics and Supply Chain Management, 1*(2), 151–169.
Fikar, C., Gronalt, M., & Hirsch, P. (2016). A decision support system for coordinated disaster relief distribution. *Expert Systems with Applications, 57,* 104–116.
Ghafory-Ashtiany, M., & Hosseini, M. (2008). Post-Bam earthquake: recovery and reconstruction. *Natural Hazards, 44*(2), 229–241.
Goldschmidt, K. H., & Kumar, S. (2019). Reducing the cost of humanitarian operations through disaster preparation and preparedness. *Annals of Operations Research*, 1–14.
Gunasekaran, A., Dubey, R., Fosso Wamba, S., Papadopoulos, T., Hazen, B. T., & Ngai, E. W. (2018). Bridging humanitarian operations management and organisational theory. *International Journal of Production Research, 56*(21), 6735–6740.
Hajipour, V., Mehdizadeh, E., & Tavakkoli-Moghaddam, R. (2014). A novel Pareto-based multi-objective vibration damping optimization algorithm to solve multi-objective optimization problems. *Scientia Iranica–Transaction E, 21*(6), 2368–2378.
He, F., & Zhuang, J. (2016). Balancing pre-disaster preparedness and post-disaster relief. *European Journal of Operational Research, 252*(1), 246–256.
Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N., & Wachtendorf, T. (2012). On the unique features of post-disaster humanitarian logistics. *Journal of Operations Management, 30*(7–8), 494–506.
Jin, S., Jeong, S., Kim, J., & Kim, K. (2015). A logistics model for the transport of disaster victims with various injuries and survival probabilities. *Annals of Operations Research, 230*(1), 17–33.
Kelle, P., Schneider, H., & Yi, H. (2014). Decision alternatives between expected cost minimization and worst case scenario in emergency supply—Second revision. *International Journal of Production Economics, 157,* 250–260.

Khayal, D., Pradhananga, R., Pokharel, S., & Mutlu, F. (2015). A model for planning locations of temporary distribution facilities for emergency response. *Socio-Economic Planning Sciences, 52,* 22–30.

Kilci, F., Kara, B. Y., & Bozkaya, B. (2015). Locating temporary shelter areas after an earthquake: A case for Turkey. *European Journal of Operational Research, 243*(1), 323–332.

Kovács, G., & Spens, K. (2009). Identifying challenges in humanitarian logistics. *International Journal of Physical Distribution & Logistics Management, 39*(6), 506–528.

Li, A. C., Nozick, L., Xu, N., & Davidson, R. (2012). Shelter location and transportation planning under hurricane conditions. *Transportation Research Part E: Logistics and Transportation Review, 48*(4), 715–729.

Lin, Y. H., Batta, R., Rogerson, P. A., Blatt, A., & Flanigan, M. (2012). Location of temporary depots to facilitate relief operations after an earthquake. *Socio-Economic Planning Sciences, 46*(2), 112–123.

Liu, Y., Lei, H., Wu, Z., & Zhang, D. (2019). A robust model predictive control approach for post-disaster relief distribution. *Computers & Industrial Engineering, 135,* 1253–1270.

Mehdizadeh, E., & Tavakkoli-Moghaddam, R. (2008). Vibration damping optimization. In *Proc. of the Int. Conf. Operations Research 2008 – OR and Global Business*, Germany, 3–5 September 2008.

Mehdizadeh, E., Tavakkoli-Moghaddam, R., & Yazdani, M. (2015). A vibration damping optimization algorithm for a parallel machines scheduling problem with sequence-independent family setup times. *Applied Mathematical Modelling, 39*, 6845–6859.

Memari, P., Tavakkoli-Moghaddam, R., Partovi, M., & Zabihian, A. (2018). Fuzzy dynamic location-allocation problem with temporary multi-medical centers in disaster management. *IFAC-Papers OnLine., 51*(11), 1554–1560.

Movahedi, H. (2005). Search, rescue, and care of the injured following the 2003 Bam, Iran, earthquake. *Earthquake Spectra, 21*(1_suppl), 475–485.

Najafi, M., Eshghi, K., & Dullaert, W. (2013). A multi-objective robust optimization model for logistics planning in the earthquake response phase. *Transportation Research Part E: Logistics and Transportation Review, 49*(1), 217–249.

Ni, W., Shu, J., & Song, M. (2018). Location and emergency inventory pre-positioning for disaster response operations: Min–max robust model and a case study of Yushu earthquake. *Production and Operations Management, 27*(1), 160–183.

Noyan, N. (2012). Risk-averse two-stage stochastic programming with an application to disaster management. *Computers & Operations Research, 39*(3), 541–559.

Onan, K., Ülengin, F., & Sennaroğlu, B. (2015). An evolutionary multi-objective optimization approach to disaster waste management: A case study of Istanbul Turkey. *Expert Systems with Applications, 42*(22), 8850–8857.

Özdamar, L., Ekinci, E., & Küçükyazici, B. (2004). Emergency logistics planning in natural disasters. *Annals of Operations Research, 129*(1), 217–245.

Paul, D., Zhang, A. N., & Asian, S. (2018). On the value of demand management for mitigating risk: peak-order reduction through trend filtering. In *Proceedings of the 2018 IEEE international conference on systems, man, and cybernetics (SMC)*, Miyazaki, Japan, 7–10 October 2018, (pp. 2260–2265). IEEE.

Paul, J. A., & MacDonald, L. (2016). Location and capacity allocations decisions to mitigate the impacts of unexpected disasters. *European Journal of Operational Research, 251*(1), 252–263.

Paul, S. K., Asian, S., Goh, M., & Torabi, S. A. (2019). Managing sudden transportation disruptions in supply chains under delivery delay and quantity loss. *Annals of Operations Research, 273*(1–2), 783–814.

Pérez-Rodríguez, N., & Holguín-Veras, J. (2016). Inventory-allocation distribution models for postdisaster humanitarian logistics with explicit consideration of deprivation costs. *Transportation Science, 50*(4), 1261–1285.

Pyakurel, U., Nath, H. N., & Dhamala, T. N. (2019). Partial contraflow with path reversals for evacuation planning. *Annals of Operations Research, 283*(1–2), 591–612.

Rath, S., & Gutjahr, W. J. (2014). A math-heuristic for the warehouse location–routing problem in disaster relief. *Computers & Operations Research, 42,* 25–39.

Raziei, Z., Tavakkoli-Moghaddam, R., Rezaei-Malek, M., Bozorgi-Amiri, A., & Jolai, F. (2018). Postdisaster relief distribution network design under disruption risk: A tour covering location-routing approach. In P. Samui, D. Kim, C. Ghosh (Eds.) *Global case studies in mitigation and recovery*, Chapter 23, (pp. 393–406). Elsevier.

Rezaei Somarin, A., Asian, S., Jolai, F., & Chen, S. (2018). Flexibility in service parts supply chain: A study on emergency resupply in aviation MRO. *International Journal of Production Research, 56*(10), 3547–3562.

Rezaei-Malek, M., Tavakkoli-Moghaddam, R., Cheikhrouhou, N., & Taheri-Moghaddam, A. (2016). An approximation approach to a trade-off among efficiency, efficacy, and balance for relief pre-positioning in disaster management. *Transportation Research Part E: Logistics and Transportation Review, 93,* 485–509.

Rodríguez-Espíndola, O., Albores, P., & Brewster, C. (2018). Disaster preparedness in humanitarian logistics: A collaborative approach for resource management in floods. *European Journal of Operational Research, 264*(3), 978–993.

Sabouhi, F., Bozorgi-Amiri, A., Moshref-Javadi, M., & Heydari, M. (2019). An integrated routing and scheduling model for evacuation and commodity distribution in large-scale disaster relief operations: a case study. *Annals of Operations Research, 283*(1–2), 643–677.

Saeidian, B., Mesgari, M. S., & Ghodousi, M. (2016). Evaluation and comparison of genetic algorithm and bees algorithm for location–allocation of earthquake relief centers. *International Journal of Disaster Risk Reduction, 15,* 94–107.

Sazvar, Z., Zokaee, M., Tavakkoli-Moghaddam, R., Salari, S. A., & Nayeri, S. (2021). Designing a sustainable closed-loop pharmaceutical supply chain in a competitive market considering demand uncertainty, manufacturer's brand and waste management. *Annals of Operations Research*, Article in Press.

Sharma, B., Ramkumar, M., Subramanian, N., & Malhotra, B. (2019). Dynamic temporary blood facility location-allocation during and post-disaster periods. *Annals of Operations Research, 283*(1), 705–736.

Sheu, J. B. (2007). An emergency logistics distribution approach for quick response to urgent relief demand in disasters. *Transportation Research Part E: Logistics and Transportation Review, 43*(6), 687–709.

Somarin, A. R., Asian, S., & Chen, S. (2016). Dynamic priority repair policy for service parts supply chain. In *Proceedings of the 2016 IEEE international conference on industrial engineering and engineering management (IEEM)*, Bali, Indonesia, 4–7 December 2016 (pp. 798–802). IEEE.

Somarin, A. R., Chen, S., Asian, S., & Wang, D. Z. (2017). A heuristic stock allocation rule for repairable service parts. *International Journal of Production Economics, 184,* 131–140.

Tofighi, S., Torabi, S. A., & Mansouri, S. A. (2016). Humanitarian logistics network design under mixed uncertainty. *European Journal of Operational Research, 250*(1), 239–250.

Toyasaki, F., Arikan, E., Silbermayr, L., & Falagara Sigala, I. (2017). Disaster relief inventory management: Horizontal cooperation between humanitarian organizations. *Production and Operations Management, 26*(6), 1221–1237.

Tricoire, F., Graf, A., & Gutjahr, W. J. (2012). The bi-objective stochastic covering tour problem. *Computers & Operations Research, 39*(7), 1582–1592.

Van Wassenhove, L. N. (2006). Humanitarian aid logistics: Supply chain management in high gear. *Journal of the Operational Research Society, 57*(5), 475–489.

Whybark, D. C. (2007). Issues in managing disaster relief inventories. *International Journal of Production Economics, 108*(1–2), 228–235.

Yang, F., Yuan, Q., Du, S., & Liang, L. (2016). Reserving relief supplies for earthquake: A multi-attribute decision making of China Red Cross. *Annals of Operations Research, 247*(2), 759–785.

Zahiri, B., Torabi, S. A., & Tavakkoli-Moghaddam, R. (2017). A novel multi-stage possibilistic stochastic programming approach (with an application in relief distribution planning). *Information Sciences, 385,* 225–249.

Zhu, L., Gong, Y., Xu, Y., & Gu, J. (2019). Emergency relief routing models for injured victims considering equity and priority. *Annals of Operations Research, 283*(1), 1573–1606.

Zokaee, S., Bozorgi-Amiri, A., & Sadjadi, S. J. (2016). A robust optimization model for humanitarian relief chain design under uncertainty. *Applied Mathematical Modelling, 40*(17–18), 7996–8016.

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