Soft Computing
https://doi.org/10.1007/s00500-023-09184-8

OPTIMIZATION

A location-inventory-distribution model under gradual injection of pre-disaster budgets with application in disaster relief logistics: a case study

Leyla Fazli[1] · Majid Salari[1] · Hossein Neghabi[1]

Accepted: 28 August 2023

Abstract

Natural disasters lead to massive human and financial losses yearly; thus, disaster planning is of critical importance. One of the most crucial measures for disaster planning is developing an efficient disaster relief supply chain (DRSC) network. Thus, many researchers have focused on this field while overlooking some crucial actual conditions as a result of the complexity of the problem. Consequently, this study develops a DRSC network considering the perishability of relief commodities (RCs), the gradual injection of the limited pre-disaster budgets, pre-disaster lateral transportation, and the time value of money. In this respect, a novel multi-period multi-commodity mixed-integer non-linear programming model is presented, which optimizes pre-disaster warehouse location and inventory management and the post-disaster re-procurement and distribution of RCs in each period. Utilizing a new service utility index, the proposed model strives to minimize deprivation cost while maximizing demand coverage and fair service. To provide the required RCs in the pre-disaster phase, a bidirectional quantity flexibility contract (BQFC) is proposed, which is integrated with multi-sourcing and allows for two-part buybacks, installment and delayed payments, and quantity-based discounts on its terms. The applicability and performance of the model are validated via a real case study in Mashhad, Iran. Various sensitivity analyses are provided to highlight the desirable performance of the model and achieve helpful managerial insights.

Keywords Humanitarian relief supply chain · Location-inventory-distribution problem · Gradual budget injection · Bidirectional quantity flexibility contract · Perishability · Time value of money

1 Introduction

On the one hand, the increase in the number of natural disasters and the expansion of their destructive range, and on the other hand, population growth in different areas of the world have increased economic losses and human casualties caused by such incidents. According to the Natural Disaster Database, 387 natural disasters occurred worldwide in 2022, resulting in 30,704 deaths, affecting 185 million people, and leading to 223.8 billion dollars in financial losses (EM-DAT, www.emdat.be). One example of the most recent and tragic disasters is the 7.8-magnitude earthquake in Nepal in April 2015, which was followed by severe aftershocks for more than 1 month and led to about 8,000 deaths and more than 2.8 million people needing help (Maharjan and Hanaoka 2017). Also, about 200,000 and 225,000 people were killed in the 2010 Haiti earthquake and the 2004 Indian Ocean tsunami, respectively (Altay and Green 2006; Ergun et al. 2014).

The losses caused by disasters cannot be compensated in various aspects, especially the human aspect; however, with preventive measures and proper planning to prepare for coping with such incidents, these losses can be reduced as much as possible. Therefore, a research branch called the humanitarian relief supply chain (HRSC) has been

✉ Majid Salari
msalari@um.ac.ir

Leyla Fazli
leyla.fazli@yahoo.com

Hossein Neghabi
hosseinneghabi@um.ac.ir

1 Department of Industrial Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

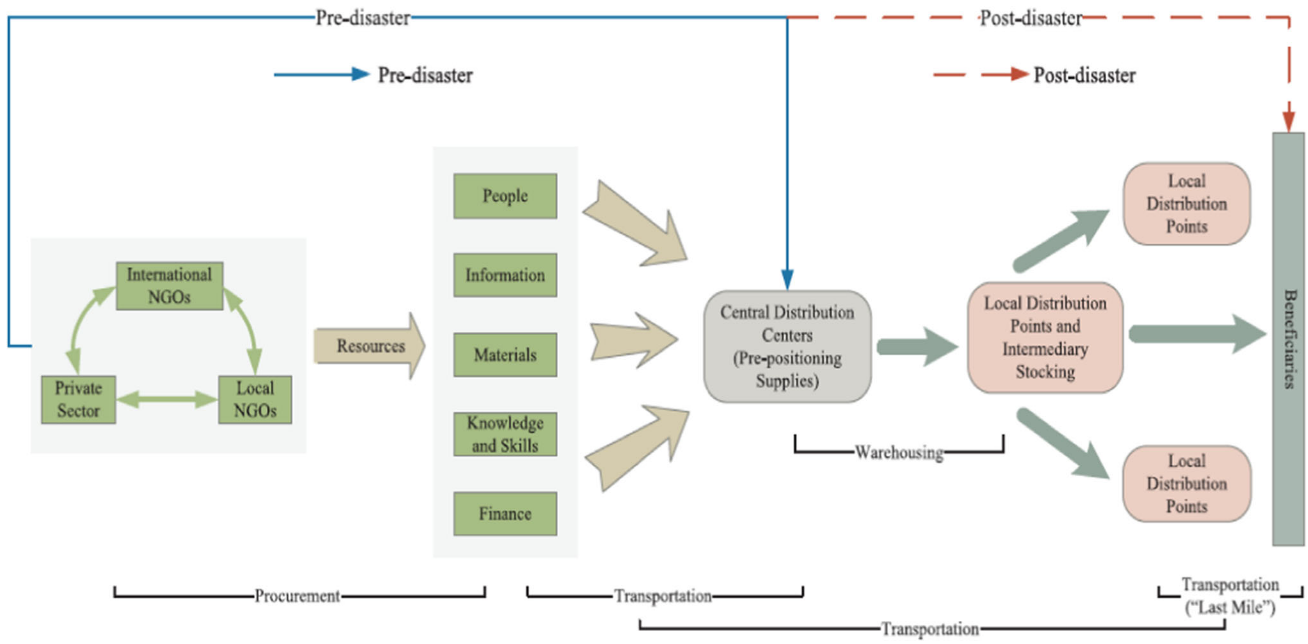

Fig. 1 HRSC structure (Li et al. 2018)

created. HRSCs usually require procurement, storage, human resources, machinery and equipment, and transportation of food, water, and medicine. HRSCs also involve various operations, which have been categorized into four phases, including mitigation, preparedness, response, and recovery (McLoughlin 1985). The preparedness and mitigation phases are concerned with pre-disaster activities, such as stockpiling of necessary RCs. In contrast, the response and recovery phases pertain to post-disaster activities, such as distributing RCs and evacuating affected individuals (McLoughlin 1985). Noteworthy, the preparedness phase relates to those operations provided for a plausible calamity, whereas the mitigation phase aims to prevent the occurrence of a calamity (Kovács and Spens 2007). In addition, administering finite resources for emergency responses and returning the affected areas to ordinary situations are carried out in the response and recovery phases, respectively (Çelik et al. 2012). Figure 1 shows the HRSC structure (Li et al. 2018).

Facilities location, inventory management, network flow, routing, scheduling, evacuation of people, and emergency settlement are among the significant activities in HRSC; as a result, HRSC is the most costly part of disaster relief operation (about 80%) (Tomasini and Van Wassenhove 2009). According to Falasca and Zobel (2011), approximately 65% of HRSC expenses are related to procurement operations, 15% to transportation, 10% to human resources, and 10% to administration.

As a result, HRSC represents a vital and critical lever for improving cost, quality, and time in the discussion of crisis management.

The shortage of RCs in affected spots leads to increased human losses. Therefore, designing and developing an effective strategy for expediting the transfer of RCs to affected spots is very important in coping with disasters. The proper location for stocking RCs, effective planning for preparing RCs in the pre-disaster phase, and designing an efficient network for distributing RCs following a disaster can be suggested as a solution. These strategies can reduce response time and relevant costs, and any incorrect measures in these areas lead to a dramatic increase in human and financial losses. Besides, a lack of attention to the interactions among HRSC phases can be a considerable obstacle to useful reactions to a crisis. Optimizing the activities of these phases separately cannot necessarily lead to optimizing the entire relief and rescue operation; it may sometimes lead to impractical decisions. As a result, integrating the HRSC phases is crucial when designing a DRSC network. Subsequently, due to the growing importance of crisis management in today's world, this study aims to design an effective and efficient DRSC network to plan preparedness and response phases. In particular, the proposed problem models decisions related to locations and establishment times of warehouses, multi-sourcing[1] based on a proposed supply contract, inventories planning and management in the pre-disaster phase, and the distribution and re-procurement of RCs in the post-disaster

[1] It is a special case of the supplier selection problem, which determines which suppliers should be selected and how much should be purchased from each selected supplier.

phase. In addition, we evaluate the model on a real case study in Mashhad City, Iran.

The rest of the study is organized as follows: Some of the most relevant research and the main motivations and contributions behind the current research are provided in Sect. 2. The problem under study and the proposed mathematical programming model are described in Sect. 3. A case study, along with the performance evaluation of the model, is presented in Sect. 4. Eventually, concluding statements, critical managerial insights, and recommendations for future research are expressed in Sect. 5.

2 Literature review

As the growing trend of crises has attracted increasing attention to HRSCs, numerous researches have recently been undertaken in this realm. In the following, we review some of the most relevant publications to the current study.

Moreno et al. (2016) proposed two programming models to integrate and coordinate location, distribution, and fleet sizing decisions in the post-disaster under an uncertain, multi-commodity, multi-period, and multi-modal environment. To save overall resources and improve service levels, one of the models considered the option of reusing vehicles to cover extra routes within the same period. The findings revealed that integrating the decisions in a multi-period environment and the option of reusing vehicles diminish the total cost.

In light of the importance and yet lack of behavioral research in humanitarian relief operations (Sankaranarayanan et al. 2018), Espejo-Díaz and Guerrero (2021) extended their previous research (2020) by considering human behaviors such as victims' word of mouth and impatience. They studied a dynamic post-disaster relief distribution problem considering donations, formulated as an inventory routing problem. Due to the possibility of happening aftershocks or new disaster events (i.e., secondary disasters), they attempted to minimize the risk of losing inventory, in addition to inventory shortages. The findings disclosed that neglecting the behavioral factors results in the highest inventory shortages in the HRSC.

Ghasemi et al. (2022a, b, c) determined the optimal locations and capacities of shelters and warehouses, homeless people, injured people, corpses, relief staff, vehicles, and RCs flows, and the best routes for the evacuation of victims in the post-disaster phase by developing a simulation–optimization model. They minimized the total probability of unsuccessful evacuation in routes and the maximum number of unsatisfied demands for relief staff, in addition to the total cost.

Ghasemi et al. (2022a, b, c) introduced a new mathematical model based on simulation and a cooperative game theory of coalition type to optimize location, inventory, distribution, routing, vehicle fleet, the transfer of injured people, and movement scheduling decisions at post-disaster under earthquake conditions. They also paid attention to the reliability of routes and the priority of RCs.

The following studies have determined locations for pre-positioning RCs, scheduled the procurement and storage of required RCs before the disaster, and adjusted the distribution plan of RCs in the response phase.

Li et al. (2018) presented a cooperative maximal covering location model in which RCs were prioritized.

Sanci and Daskin (2019) proposed a bi-level stochastic programming model under backlogged shortages to integrate location, storage, damaged routes restoration, distribution, and routing decisions. They showed that integrating location and network restoration models results in a significant improvement in satisfied demand and cost.

Wang and Nie (2019) proposed two mathematical models considering traffic congestion and a criticality weight for each RC.

To measure the earthquake resistance of each demand point, Wang et al. (2020) introduced a seismic resilience function calculated using fault tree analysis, analytic hierarchy process, fuzzy set theory, and neural network methods. In particular, they attempted to provide more service to the demand point that has a higher undesirable value for the seismic resilience function.

Wang et al. (2021a, b) examined the effect of the direct transfer of pre-positioned RCs among warehouses (lateral transportation[2]) in the post-disaster phase on their model. They showed that post-disaster lateral transportation leads to more flexibility and lower costs.

Unlike Abazari et al. (2021), who accounted for perishability when planning post-disaster distributions, Tavana et al. (2018), Akbarpour et al. (2020), and Sheikholeslami and Zarrinpoor (2023) looked into the inventory management of perishable RCs prior to the disaster. They made the supposition that if the supply's remaining lifespan is less than a certain threshold, it can be sold (sale mechanism; Tavana et al., and Sheikholeslami and Zarrinpoor) or sold back to the suppliers (buyback mechanism; Akbarpour et al.) at pre-disaster. Unlike Akbarpour et al., the others also made decisions about the lifespan of purchased RCs. Tavana et al. modeled the distribution of RCs within the network as a multi-echelon multi-depot vehicle routing problem. Akbarpour et al. determined locations for mobile pharmacies at each post-disaster period using a cooperative coverage mechanism, in addition to determining locations for warehouses and their size at the pre-disaster phase. To provide essential medical commodities,

[2] Lateral transportation refers to horizontal transportation within the same echelon.

they presented a multi-sourcing mechanism based on option (OC)[3] and buyback (BC)[4] contracts with the pre-positioning policy only applied to critical RCs. Moreover, they assumed that RCs have different priorities in each affected area; lead time is considerable and time-dependent, and there must always be a safety inventory for each RC in each warehouse during each pre-disaster period. Abazari et al. took account of various vehicles and determined the needed number of each vehicle and the type of vehicle of each transportation. They presumed that a perishable commodity would decay if its travel time (including loading and unloading times) exceeded a certain amount in the post-disaster phase. Managing the transfer of injured people, victims' accommodation, vehicle fleet, and human resources were other primary concerns of Sheikholeslami and Zarrinpoor.

Condeixa et al. (2017), Torabi et al. (2018), Aslan and Çelik (2019), Cotes and Cantillo (2019), Hu and Dong (2019), Akbarpour et al. (2020), Boostani et al. (2020), Nezhadroshan et al. (2021), Ghasemi et al. (2022a, b, c), and Aghajani et al. (2023) focused on the procurement of RCs in both the response and preparedness phases. Condeixa et al. considered RCs donated in the response phase. Torabi et al. presented a two-stage scenario-based mixed possibilistic-stochastic programming model considering monetary donations in the post-disaster budget. To procure RCs, they combined a multi-sourcing problem with a quantity flexibility contract (QFC).[5] Hu and Dong took into account price discounts based on delivery time and order quantity, as well as physical inventory as supplier selection criteria. In addition, it was assumed that the commodities purchased from suppliers after a disaster are either being produced by suppliers or sent from the suppliers' warehouses (their physical inventory). Since suppliers' physical inventory is initially planned to serve their regular customers, the relief organization (RO) would pay a fine to suppliers for using their physical inventory to compensate for the risk of losing these customers. In the response phase, Aslan and Çelik addressed decisions on transportation, repairing damaged roads, and the arrival time of RCs at the demand point, in addition to how to re-procure and distribute RCs. They attempted to minimize the total response time by considering three approaches based on efficacy, equity,[6] and robustness. The results demonstrated that equity-based objective outperforms its counterparts. Cotes and Cantillo optimized human suffering by minimizing the total social cost.[7] The outcomes indicated that deprivation costs represent more than 50% of the total social cost. Boostani et al. took into account the ecological effects of the packaging of RCs and CO_2 emissions in the proposed network shipments and tried to minimize these effects. Nezhadroshan et al. considered secondary disasters and also decided on the transportation mode of some network shipments at post-disaster. Moreover, their model maximized the resilience level of each relief facility estimated using fuzzy analytic network process and fuzzy decision-making trial and evaluation laboratory techniques. Ghasemi et al. designed a humanitarian relief network to manage the blood supply chain in disaster situations. Aghajani et al. introduced a procurement-warehousing-distribution model under supply disruption. The model sets up a number of multi-period QFCs with primary suppliers, a number of dynamic OCs with backup suppliers, and a multi-period warehousing contract with a third party providing warehousing service. Post-disaster decisions included order quantities from the primary and backup suppliers, the adjustment of storage needs, as well as the distribution quantities of RCs in the designed network.

In view of the intricate and unpredictable nature of catastrophes, Condeixa et al. (2017), Bai et al. (2018), Elçi and Noyan (2018), Aslan and Çelik (2019), Akbarpour et al. (2020), Chen (2020), Erbeyoğulu and Bilge (2020), Li et al. (2020), Nezhadroshan et al. (2021), Wang et al. (2021a, b), Ghasemi et al. (2022a, b, c), Noyan et al. (2022), and Zhang et al. (2022) utilized robust optimization methods to develop the problem under consideration. Condeixa et al. proposed a mean-conditional value at risk (CVaR) two-stage stochastic programming model. Bai et al. developed a fuzzy programming model with a VaR objective, credibility constraints, and fuzzy parameters defined with variable possibility distributions to solve their

[3] In an OC, a specific quantity of the suppliers' inventory can be reserved.

[4] A BC allows the buyer to return commodities up to the quantity of the initial purchase at an identical price for each unit.

[5] A QFC supplies the commodity up to a certain pre-agreed amount in excess of the initial order quantity.

[6] The concept of equity and how to measure it have been widely investigated in the literature. Braveman and Gruskin (2003) defined equity as the lack of systematic disparities among groups of people.

Footnote 6 continued
The consideration of the equity concept in allocation/distribution decisions represents supplying demand points in a fair manner, as well as the best efforts to ensure that the required relief commodities are equally distributed among all demand points. Fair relief distribution among demand points is also an important point in HRSC (Beamon and Balcik 2008). The three main approaches frequently used to achieve equity as an objective in relief distribution include: 1. Minimax approach, 2. Maximin approach, and 3. Maxisum approach (Ransikarbum and Mason 2016).

[7] Social cost includes both logistics costs and deprivation costs. Deprivation costs include the costs imposed on casualties due to lack of access to required items or services (Holguín-Veras et al. 2013); consequently, these costs represent human suffering. Given the importance of deprivation costs in HRSC, certain researchers including Holguín-Veras have focused on how to estimate deprivation cost for each person affected by a disaster and have presented different deprivation cost functions.

problem. To get variable possibility distributions for type-2 fuzzy variables, they applied the credibility critical value reduction technique. Elçi and Noyan presented a chance-constrained mean-CVaR stochastic model. In this study, lost shortages are only possible in specific scenarios where the sum of the probabilities of their occurrence is less than or equal to a certain amount. A min–max robust model was presented by Aslan and Çelik, and Akbarpour et al. To compare stochastic models with Ψ-expander models, Chen first proposed a risk-neutral stochastic bi-level programming model with known demand distributions. Then, assuming that we merely know that demand varies within a specific interval, he reformulated the model into another model called the risk-averse Ψ-expander model. The obtained results indicated that Ψ-expander models, in comparison to stochastic models, can significantly reduce the shortage cost. Erbeyoğlu and Bilge proposed a robust two-stage stochastic programming model. They optimized the locations and sizes of distribution centers in the response phase, in addition to locating warehouses before the disaster. They defined a service coverage window for demand points and assumed that each must be allocated to the nearest distribution center that can cover it. In addition, they determined several service coverage windows for distribution centers and assumed that the demand of each distribution center for each item needs to be fulfilled more than a certain amount within each service coverage window by warehouses that can cover it. Li et al. presented a three-stage scenario-based mixed robust-stochastic programming model considering secondary disasters. They also planned victims' accommodation and indicated that considering secondary disasters could lead to a significant improvement in the fulfilled demand. According to the approach presented by Mulvey et al. (1995), Nezhadroshan et al. and Ghasemi et al. proposed a robust two-stage possibilistic-stochastic programming model and a robust two-stage stochastic programming model, respectively. Wang et al. prioritized RCs and modeled their problem as a bi-level distributionally robust programming model based on the worst-case mean-CVAR criterion. They demonstrated that the suggested model outperforms its stochastic equivalent in terms of objective value and solution stability. Noyan et al. introduced a risk-averse two-stage stochastic programming model by considering a constraint according to CVAR. Zhang et al. employed a distributionally robust programming model that performs better than its stochastic equivalent.

Table 1 summarizes the above-mentioned body of research and highlights the gaps observed in the problem under study and the key distinctions between these studies and the present research.

2.1 Gap analysis and contributions

Besiou and Van Wassenhove (2020) highlighted the challenges in matching practitioner needs with academic publications and outlined the great opportunities for impactful and relevant studies. Hence, according to Besiou and Van Wassenhove's researches, other studies undertaken, as well as interviews conducted with administrative managers in Mashhad's ROs, we attempt to reduce the gaps observed in the problem under study. As a result, the followings are the significant contributions of our research that have not yet been addressed in the HRSC literature:

- Despite the large number of researches conducted in HRSCs, actual conditions have been overlooked in many inquiries as a result of the complexity of the problem (Kunz et al. 2017; Besiou and Van Wassenhove 2020). In particular, budget constraints in pre-disaster planning have been only considered in a few studies in this field. Moreover, in all these studies, budget injection into the project is instantaneous, i.e., we will have access to the total budget at the beginning of the pre-disaster planning time horizon (PTH). In practice, the total budget can be gradually made available over time (gradual budget injection). Therefore, limited budgets gradually injected into the project over the pre-disaster PTH are considered in the present study. Accordingly, the pre-disaster PTH is divided into several periods, and as a consequence, location, inventory management, and distribution problems are modeled dynamically. It is noteworthy that in the researches conducted on HRSC, the relief facilities have been established simultaneously prior to the disaster; as a result, the location problem has been modeled as a static one. However, in actual conditions, the simultaneous establishment of the necessary relief facilities before the disaster cannot be possible due to various reasons, such as shortage of financial resources, and lack of human resources.
- Selecting the proper suppliers and optimally allocating the order to them (multi-sourcing) will result in lower purchasing costs and more efficient and effective disaster response. Also, making agreements with suppliers prior to a disaster not only ensures the accessibility and affordable procurement of required RCs but also leads to lower holding costs and enhances the reliability of timely delivery and flexibility for coping with the high uncertainty of demand following a disaster. However, a few studies have planned the procurement of RCs using a multi-sourcing problem based on supply contracts. To plan the procurement and inventory of perishable RCs, we devise a multi-sourcing procedure based on a supply contract

Table 1 A comparison of the features of the proposed model with the most relevant studies in the HRSC literature

Relevant studies	MC		MP		TODR			POC	TVOM	TOU					TOD										
	P	S	PP	RP	SU	RF	TN			SS	SP	R	F	H	L	I	D	VF	RO	VA	TI	SC	HR	RE	O
Moreno et al. (2016)		*		*		*	*			*					○		*	○							
Condeixa et al. (2017)		*				*	*			*					*	■	*								
Bai et al. (2018)		*				*	*						*	*	*	*	*								
Elçi and Noyan (2018)	*					*	*			*					*	*	*								
Li et al. (2018)		*								*					*	*	*								
Tavana et al. (2018)		*	*			*		*							*	*	*		○						
Torabi et al. (2018)		*								*			*	*	*	■	*								
Aslan and Çelik (2019)		*				*	*			*					*	■	*		○			○		*	
Cotes and Cantillo (2019)		*													*	*	*								
Hu and Dong (2019)					*	*				*					*	■	*								
Sanci and Daskin (2019)	*			*		*	*			*				*	*	*	*							*	
Wang and Nie (2019)		*				*	*			*					*	*	*								
Akbarpour et al. (2020)		*	*	*				*		*		*			■	■	*								
Boostani et al. (2020)		*			*	*	*			*					*	■	*								
Chen (2020)		*									*	*			*	*	*								
Erbeyoğlu and Bilge (2020)		*								*					■	*	*								
Li et al. (2020)		*					*			*				*	*	*	*			*					
Wang et al. (2020)		*				*				*					*	*	*								
Abazari et al. (2021)		*					*	*			*		*		*	*	*	○							
Espejo-Díaz and Guerrero (2021)				*		*											*	○	○						
Nezhadroshan et al. (2021)		*			*	*	*			*			*	*	*	■	*	○							
Wang et al. (2021a, b)		*				*				*					*	*	*								
Wang et al. (2021a, b)		*								*				*	*	*	*								
Ghasemi et al. (2022a, b, c)		*		*		*				*					*	■	*								
Ghasemi et al. (2022a, b, c)		*		*		*				*				*	○	○	*	○	○	*	*		○		○
Ghasemi et al. (2022a, b, c)		*		*			*			*				*	○	○	*	○	○		*	○			
Noyan et al. (2022)	*					*				*					*	*	*								
Zhang et al. (2022)		*				*						*			*	*	*								
Sheikholeslami and Zarrinpoor (2023)		*	*					*					*		*	*	*	■		*	*		■		
Aghajani et al. (2023)		*		*	*	*	*			*					*	■	*								*

Table 1 (continued)

Relevant studies	MC		MP		TODR			POC	TVOM	TOU					TOD										
	P	S	PP	RP	SU	RF	TN			SS	SP	R	F	H	L	I	D	VF	RO	VA	TI	SC	HR	RE	O
Present work		*	*			*	*	*	*	*				*	*	■	*								

Relevant studies	MS		SC	SD	LT		TOLM			TOOF						TOC			TOPM				HA / MHA	CS
	PP	RP			PP	RP	ME	CE	CO	C	DC	T	DI	E	O	BB	BA	E	NL	MI	ML	MO		
Moreno et al. (2016)							*			*									*	*			*	*
Condeixa et al. (2017)							*		*	*								*		*	*			*
Bai et al. (2018)						*	*			*										*				
Elçi and Noyan (2018)						*	*		*	*								*		*				*
Li et al. (2018)							*		*		*					*	*	*		*				
Tavana et al. (2018)							*			*		*				*				*		*	*	*
Torabi et al. (2018)	*	*	*				*			*						*	*			*			*	*
Aslan and Çelik (2019)							*	*				*		*		*	*		*	*	*		*	*
Cotes and Cantillo (2019)		*					*		*	○				*				*	*	*				*
Hu and Dong (2019)	*	*		*			*			*										*				*
Sanci and Daskin (2019)						*	*			*										*	*		*	*
Wang and Nie (2019)						*	*			*									*	*				*
Akbarpour et al. (2020)	*	*	*				*	*	*	*				■				*	*	*		*		*
Boostani et al. (2020)	*	*					*	*		*				■	*				*	*		*		*
Chen (2020)							*		*	*								*	*	*	*		*	*
Erbeyoğlu and Bilge (2020)							*		*	*								○		*				*
Li et al. (2020)							*			*										*			*	*
Wang et al. (2020)	*						*			*								■	*	*			*	*
Abazari et al. (2021)							*	*	*	*			*	*	*			*	*	*		*	*	*
Espejo-Díaz and Guerrero (2021)											*				*					*		*		*
Nezhadroshan et al. (2021)		*					*	*		*				*	*					*		*		*
Wang et al. (2021a, b)						*	*		*	*								*		*				*
Wang et al. (2021a, b)							*		*	*						*		*		*	*			*
Ghasemi et al. (2022a, b, c)	*	*				*	*			*	*									*		*		
Ghasemi et al. (2022a, b, c)							*			*				*	*				*	*		*	*	*
Ghasemi et al. (2022a, b, c)							*			*		*			*					*		*	*	*

Table 1 (continued)

Relevant studies	MS		SC	SD	LT		TOLM			TOOF						TOC			TOPM				HA / MHA	CS
	PP	RP			PP	RP	ME	CE	CO	C	DC	T	DI	E	O	BB	BA	E	NL	MI	ML	MO		
Noyan et al. (2022)						*	*		*	*								*		*				
Zhang et al. (2022)							*			*										*				*
Sheikholeslami and Zarrinpoor (2023)							*		*	*	*								*			*	*	*
Aghajani et al. (2023)	*		*	*			*		*	*						*	*	*		*			*	*
Present work	*	*	*	*	*		*	*		■	*			■		○			*	*				*

Multi-commodity (MC): in the form of a package (P), separately (S). Multi-period (MP): in the preparedness phase (PP), in the response phase (RP(. Types of disruption risks (TODR): suppliers (SU), relief facilities (RF(, and transport network (TN(. Perishability of commodities (POC). Time value of money (TVOM). Types of uncertainties (TOU): scenario-based stochastic (SS), stochastic with known probability distribution (SP), fuzzy (F), robust (R), and combination of the previous categories (H). Types of decisions (TOD): Location (L), Inventory (I), Distribution (D), Vehicle fleet (VF), Routing (RO), Victims' accommodation (VA), Transfer of injured people (TI), Scheduling (SC), Human resources (HR), Restoration (RE), Other decisions (O), pre-disaster decision (*), post-disaster decision (○), and pre- and post-disaster decision (■)

Multi-sourcing (MS): in the preparedness phase (PP), in the response phase (RP(. Supply contract (SC). Sale discount (SD). Lateral transportation (LT): in the preparedness phase (PP) and in the response phase (RP(. Types of location models (TOLM): Median (ME), Center (CE), Covering (CO). Types of objective functions (TOOF): Cost (C): Logistics costs (*), Deprivation costs (■), Social costs (○), Demand coverage (DC), Time (T), Distance (DI), Equity (E): Equitability (*), Balance (■), Both equitability and balance (○), and Other objectives (O). Types of constraints (TOC): Budget before the disaster (BB): instantaneous budgets injection (*), Gradual budgets injection (○), Budget after the disaster (BA), Equity (E): Equitability (*), Balance (■), Both equitability and balance (○). Types of programming model (TOPM): Non-linear (NL), Mixed-integer (MI), Multi-level (ML), and Multi-objective (MO). Heuristic algorithm/Meta-heuristic algorithm (HA/MHA). Case study (CS)

mechanism that varies from prior studies in several aspects. In particular, already proposed mechanisms are QFC, OC, and BC with instant payments without delay. When it comes to managing risks, including demand uncertainty, supply unreliability, and price instability accompanied by decreasing pre-positioned inventory levels and supply expenses, QFCs are highly efficient. In addition to being flexible in orders, QFCs provide reciprocal benefits for both the seller and the buyer. In other words, under a QFC, the seller can sell additional supplies to the buyer, and the buyer can reorder the supplier without paying a reservation cost in advance (Torabi et al. 2018). Accordingly, in this paper, we design a QFC with a two-part buyback (TPB)[8] [bidirectional QFC (BQFC)], taking into account installment and delayed payments. In contrast to prior studies, which only addressed discounts on the purchase price, we account for based-quantity discounts on the various terms of our contract. Therefore, the proposed model includes important aspects of business behavior that can place this study in the category of behavioral research.

- The main objective of the HRSC is to reduce human suffering and mortality to the greatest extent. Hence, in addition to efficiency, efficacy, equity, and happiness/distress are among the most significant criteria that must be considered in HRSC models (Gutjahr and Nolz 2016). Efficiency generally comprises logistics costs, including establishment of facilities, procurement of RCs and equipment, transportation, and personnel's wages (Gutjahr and Nolz 2016). In addition, efficacy can be measured by various criteria, including coverage, travel distance, response time, security, and reliability, or a combination of them (Gutjahr and Nolz 2016). It is noteworthy that efficacy is much more important than efficiency in HRSCs, as human issues take precedence over monetary issues (Balcik and Beamon 2008).

Fair service is a natural requirement, because victims expect that there must be no privileges or priority for certain groups of people. In particular, fair service is usually described by the equity concept, which includes balance and equitability (Karsu and Morton 2015; Gutjahr and Nolz 2016). The equitability concept refers to serving groups of individuals who are indistinguishable from one another. In contrast, the balance concept refers to serving groups of individuals who are distinct in terms of their claims, needs, and preferences (Karsu and Morton 2015). Essentially, different affected areas have different demand quantities and priorities due to varied factors, such as

[8] The possibility of returning commodities such that the supplier purchases a part of the total returned commodities at a specific unit price and the rest at another unit price.

population and catastrophe intensity (Gralla et al. 2014; Nagurney et al. 2015). Therefore, to avoid a potential societal calamity, fair service should be described by the balance concept (Rezaei-Malek and Tavakkoli-Moghaddam 2014).

One of the primary and vital objectives of HRSCs is to reduce hardship, pain, affliction, deprivation, social disturbances, and negative emotions of victims, described by the distress criterion. Indeed, distress alludes to social and psychological expenses, addressed in a tiny minority of studies (Karsu and Morton 2015). In this regard, Holguín-Veras et al. (2013) introduced the notion of deprivation cost to measure the suffering of victims deprived of vital RCs. They estimated the deprivation cost as a non-decreasing convex function of deprivation time.[9]

Our developed model incorporates efficacy, equity, and distress in the objective function. Specifically, the introduced objective function indicates the desire to service the affected areas with the highest possible quantity of RCs and the lowest possible deprivation cost in the fairest possible manner. To maximize the efficacy of the HRSC network, Noham and Tzur (2018) utilized a ratio of fulfilled demand to travel time. Accordingly, this study, inspired by Holguín-Veras et al. (2016) and Noham and Tzur (2018), develops a new measure called service utility, which combines efficacy and distress and is estimated as the ratio of the fraction of fulfilled demand to deprivation cost. Since different affected areas had different demand quantities, Tzeng et al. (2007) applied the minimal amount of fraction of the total fulfilled demand among all affected areas as a balance measure. Therefore, inspired by Tzeng et al. (2007), a new balance measure is presented as the minimum amount of the total service utility among affected areas.

- This study pays attention to the time value of money by investing budgets and the variability of costs affected by inflation during the pre-disaster PTH.
- In different periods, established warehouses may not be able to stockpile adequate amounts of RCs at pre-disaster, as the procurement budget is limited. Thus, to improve service, pre-disaster lateral transportation can be an efficient and appropriate alternative under the incapacity to procure more RCs from supply resources, as transferring pre-positioned RCs among warehouses can lead to more efficient storage of procured RCs in warehouses. Indeed, pre-disaster lateral transportation helps to increase the inventory levels of more suitable warehouses by receiving RCs stored in other warehouses without incurring purchase costs, while reducing the inventory levels of less suitable warehouses.
- To demonstrate the efficiency and applicability of the suggested model, we run the model on a real case study for a plausible earthquake in Mashhad, Iran.

[9] The duration an affected person is deprived of relief commodities.

3 Problem description

In this section, we develop a model that focuses on warehouse location, inventory management, and distribution problems in line with managing an HRSC in both the preparedness and response phases. Pre-disaster warehouse location and inventory management influence the performance of relief activities as the number and locations of warehouses and the number of RCs stored in them straightly affect demand coverage, response time, and the expenses incurred all over the DRSC. The general outline of the desired DRSC network is presented in Fig. 2. Noteworthy, to bring the problem under consideration closer to reality, the proposed hypotheses have been developed based on interviews with professionals in this field, including administrative managers in Mashhad's ROs, in addition to real case studies conducted in the HRSC literature.

In this research, a specific disaster of high intensity is taken into account that its occurrence time is unknown and may occur at any time of the considered pre-disaster PTH. Therefore, the RO seeks to stockpile several critical perishable RCs (e.g., food, water, and medicine) in available warehouses prior to the disaster. These RCs are those of high priority in the immediate aftermath of a disaster that any delay in getting them to affected people might result in a great deal of discomfort for affected people or a high mortality rate.

Multiple suppliers, warehouses, and affected areas make up the DRSC network in question. Suppliers have different limited supply capacities and are safe from disaster in terms of capacity and capability. They are ordered depending on factors, such as supply capacity, contract terms, sales discounts, and travel time. Warehouses are an essential part of our DRSC network as they distribute the necessary RCs to the affected areas. Specific considerations should be taken into account when selecting warehouse sites from a list of recognized candidates, namely (I) the storage capacity and launching cost of the warehouses, and (II) the needed travel time that maintains deprivation cost to a minimum. As a result, the warehouses in our network are located near affected areas to ensure efficient and quick distribution of RCs. In addition, (III) the security of the warehouses in terms of the risk of pre-positioned RCs' destruction is taken into account as the third consideration.

Pre-disaster storage of all the required RCs imposes a high cost on the RO while enhancing responsiveness. As a result, to strike a balance between responsiveness and cost-effectiveness, the appropriate quantity of the RCs is pre-positioned in the specified warehouses. The RCs are purchased and transferred to warehouses from selected suppliers. Following the disaster, each RC's demand is estimated and if there is any shortfall, it will be acted to purchase additional RCs to minimize unsatisfied demands. The amount of RCs stored prior to the disaster would have a direct effect on the amount of additional purchases made in the aftermath of the disaster. Accordingly, the RO employs an integrative proactive–reactive supply policy in which pre-disaster inventory levels and the quantities of post-disaster procurement are both set at the same time. This supply policy develops a novel supply contract framework based on a BQFC. The framework of the proposed BQFC is depicted in Fig. 3. It is noteworthy that among the diverse designed supply contracts for business usage, QFCs are among the most appropriate ones for use in a relief situation. QFCs can decrease the buyer's post-disaster supply risk, in addition to pre-positioned inventory levels. As a result, by including a QFC in the DRSC network design, the cost-effectiveness, and responsiveness of the DRSC can be improved (Torabi et al. 2018).

According to the designed contract, the RO purchases a specific quantity of the RC before the disaster occurs (initial order) to store it at its warehouses. The supplier also undertakes to supply up to a specific pre-agreed quantity in excess of the initial order quantity (secondary order; as $\overline{\mu}\%(\acute{\mu} > 0)$ of its initial order quantity) to be able to send it to affected areas following a calamity demanded by the RO.

The incidence time of the disaster is unknown, and it may happen after a long time. Therefore, to minimize losses caused by decaying RCs, another agreement is also included in the contract under which the supplier commits to retrieve the sold commodity when a maximum of a pre-specified time of its life has elapsed. In this way, when a given amount of time remains until the expiry date of the commodity, a pre-specified quantity of it $\left(\underline{\mu}\%\left(0<\underline{\mu}<100\right)\right.$ of its initial order quantity) will be returned to the supplier at a specific price ($\overline{\tau}\%$ of its initial price) and its remainder at another price ($\underline{\tau}\%$ of its initial price; $0 < \underline{\tau} < \overline{\tau} < 100$).

In this contract, the suppliers and RO are allowed to pay for the purchase cost in arrears and installments, and quantity-based discounts (an all-unit discount scheme) on the various parts of the contract are taken into account. In particular, purchase price, percentage of secondary orders, percentage of returned commodities with a higher selling price, percentages of return price, and payment method are different aspects influenced by the amount of order.

The RO, like any other organization, faces financial restrictions; therefore, it can only devote a limited budget to establishment and procurement operations in the pre-

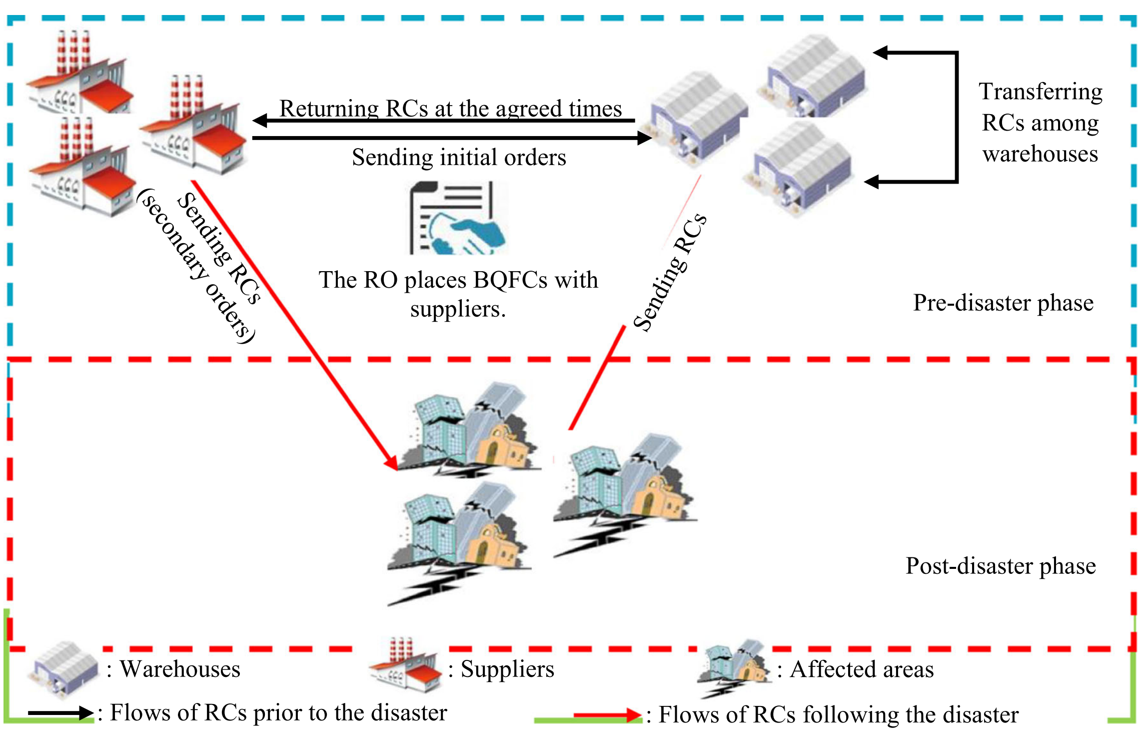

Fig. 2 General outline of the proposed DRSC

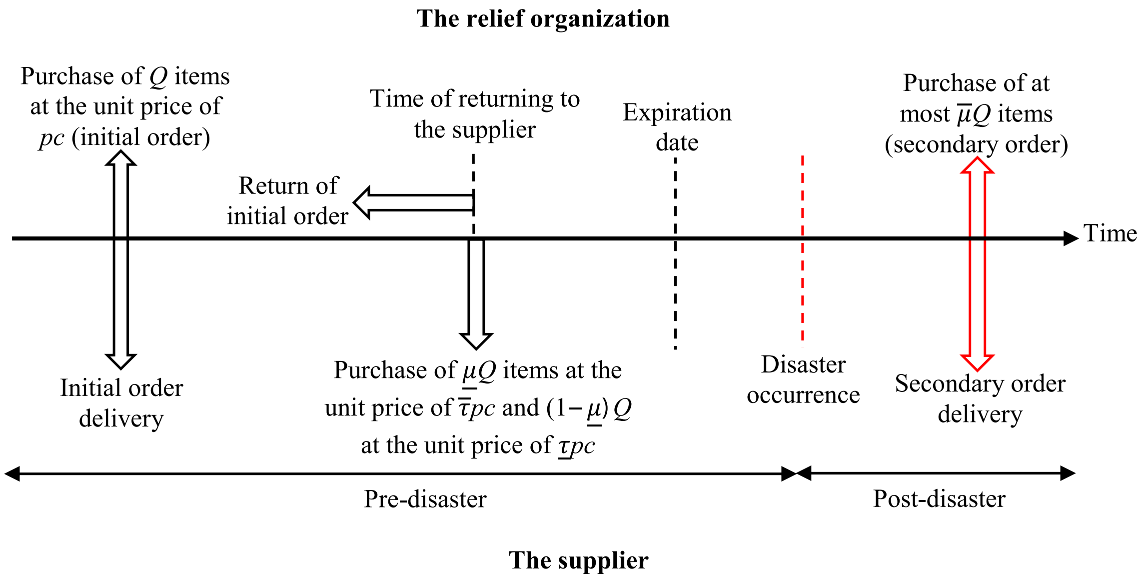

Fig. 3 Structure of the proposed BQFC

disaster phase. Of course, this budget is not fully available at the beginning of the pre-disaster PTH; instead, it gradually becomes available to the RO over time. Moreover, this budget is deposited in a bank at a specific fixed interest rate, so that it can be withdrawn at any time.

The followings are the other main hypotheses considered when formulating the model:

- o Prior to the disaster, a multi-period PTH with the same length for each period is taken into account to consider the perishability of the RCs and gradual injection of the budgets. In addition, due to the significance of quick and efficient emergency response in the first 72 h after a disaster to save victims, the post-disaster PTH is defined as a single-period horizon lasting 72 h.
- o All purchased RCs are newly manufactured, and their lead time is negligible. Consequently, the initial age of each RC is regarded as zero.
- o During the pre-disaster PTH, each warehouse can be established at most once. Once established, the warehouses are kept open until the end of the pre-disaster PTH.
- o Transfer of RCs between warehouses is only allowed before the disaster (pre-disaster lateral transportation), as warehouses may not be able to store RCs in the right amount due to the RO's limited budget, and directly sending RCs from warehouses to affected areas in the post-disaster can result in reducing response time and transportation costs.
- o Cost parameters change during the preparedness phase as affected by the inflation phenomenon.
- o Pre-disaster transportation cost is not considerable.
- o The cost of establishing a warehouse can be paid with a delay and in installments.
- o The pre-agreed duration for issuing a secondary order is equal to the length of pre-disaster periods.
- o Travel times are estimated by considering possible disruptions in the transportation network.
- o Items donated by the public are usually distributed a few days after the disaster, since they require some logistical operations before they can be distributed (such as collecting, sorting, amalgamating, and repackaging). Therefore, they are not considered for usage within the first 72 h after the disaster.
- o The deprivation cost function given by Holgun-Veritas et al. (2016), a non-decreasing convex function of deprivation time, is used to calculate deprivation cost, while deprivation time is considered equal to the travel time.

3.1 Model formulation

In this research, network design decisions in the preparedness phase include (1) locating warehouses, (2) selecting appropriate suppliers and arranging the contract with them, (3) determining the inventory levels of warehouses, and (4) transshipment quantities between warehouses at each period of the pre-disaster PTH. In the response phase, a distribution network is designed by determining the number of RCs that must be dispatched to affected areas from selected suppliers and warehouses. For this purpose, a mixed-integer non-linear programming model is developed whose notations, objective function, and constraints are as follows:

Sets and indices:

S	Set of suppliers, indexed by s
W	Set of candidate sites for establishing warehouses, indexed by $w, \acute{w}$
D	Set of affected areas, indexed by d
G	Set of commodities, indexed by g
A	Set of possible ages of commodities, indexed by a
T	Set of pre-disaster periods, indexed by t,$\acute{t}$.
O	Set of supplier-provided quantity intervals, indexed by o
P	Set of possible installments of establishment and procurement costs, indexed by p

Parameters:

ir	General inflation rate
pc_{sgot}	Unit purchase cost of commodity g from supplier s under quantity interval o at period t; $pc_{sgot} = pc_{sgo1}(1 + ir)^{t-1}$.
ec_{wt}	Cost of establishing warehouse w at period t ; $ec_{wt} = ec_{w1}(1 + ir)^{t-1}$
n_{dg}	Demand of commodity g at affected area d
ρ_{wg}	Fraction of stocked commodity g at warehouse w that remains usable at post-disaster; $0 \le \rho_{wg} \le 1$
i	Effective bank interest rate
c_{wg}	Storage capacity of warehouse w for commodity g
B	Total budget allocated to establishment and procurement operations at pre-disaster; $B = \overline{B} + \overline{\overline{B}}$.
$\overline{B}$	Total establishment budget
$\overline{b}_t$	Part of total establishment budget that is available at the start of period t;$\sum_{t\in T} \overline{b}_t = \overline{B}$
$\overline{\overline{B}}$	Total procurement budget
$\overline{\overline{b}}_t$	Part of total procurement budget that is available at the start of period t;$\sum_{t\in T} \overline{\overline{b}}_t = \overline{\overline{B}}$
β_1,β_2	Weight factors in the objective function
$\overline{t}_{wd}$	Travel time between warehouse w and affected area d
$\overline{\overline{t}}_{sdg}$	Travel time between the s^{th} supplier of commodity g and affected area d
$\acute{a}_g$	Age of commodity g for returning it
$\underline{l}_{sgo}$, $\overline{l}_{sgo}$	Lower and upper bound of quantity interval o suggested by the s^{th} supplier of commodity g
$\overline{\mu}_{sgo}$	Percentage of initial order of commodity g from supplier s under quantity interval o for determining maximum amount of secondary order
$\underline{\mu}_{sgo}\acute{a}_g$	Fraction of initial order of commodity g from supplier s under quantity interval o for determining amount of returned commodities with a higher selling price .
$\overline{\tau}_{sgo}$, $\underline{\tau}_{sgo}$	Fractions of unit purchase cost of commodity g from supplier s under quantity interval o for determining unit selling prices of returned commodities
α_{wp}	Fraction of cost of establishing warehouse w, which must be paid in the p^{th} installment;$\sum_p \alpha_{wp} = 1$
$\acute{\alpha}_{sgop}$	Fraction of initial purchase cost of commodity g from supplier s under quantity interval o, which must be paid in the p^{th} installment;$\sum_p \acute{\alpha}_{sgop} = 1$
lp	Duration of each period
tp_{wp}	Time to pay the p^{th} installment of cost of establishing warehouse w; $0 \le tp_{wp} \le lp$.
$\acute{tp}_{sgop}$	Time to pay the p^{th} installment of initial purchase cost of commodity g from supplier s under quantity interval o; $0 \le \acute{tp}_{sgop} \le lp$.
$F(\overline{t}_{wd})$, $F(\overline{\overline{t}}_{sdg})$	Deprivation cost functions; $F(\overline{t}_{wd}) = 0.9814e^{0.0188\overline{t}_{wd}}$; $F(\overline{\overline{t}}_{sdg}) = 0.9814e^{0.0188\overline{\overline{t}}_{sdg}}$
M	A large enough positive constant

Decision variables:

y_{wt}	1, if warehouse w is established at period t; 0, otherwise
x_{sgot}	1, if commodity g is purchased from supplier s under quantity interval o at period t; 0, otherwise
$k_{w\acute{w}t}$	0, if no commodities are transferred from warehouse w to warehouse $\acute{w}$ at period t; 1, otherwise
q_{sgot}	Amount of commodity g purchased from supplier s under quantity interval o at period t (initial order)
$\acute{q}_{wgt}$	Amount of commodity g sent to warehouse w from suppliers at period t
in_{wgat}	Inventory quantity of commodity g with age a in warehouse w at the start of period t
r_{wgt}	Amount of returned commodity g from warehouse w to suppliers at period t
z_{wdgt}	Amount of commodity g sent from warehouse w to affected area d when disaster struck at period t
u_{sdgt}	Amount of commodity g sent from supplier s to affected area d when disaster struck at period t (secondary order)
$h_{w\acute{w}gat}$	Amount of commodity g with age a sent from warehouse w to warehouse $\acute{w}$ at period t
$\overline{v}_t$	Net balance of establishment budget at the end of period t
$\overline{\overline{v}}_t$	Net balance of procurement budget at the end of period t

Model 1:

$$\textbf{Max} \ = \beta_1\left(\sum_{w,d,g,t}\frac{\frac{z_{wdgt}}{n_{dg}}}{F(\overline{t}_{wd})}+\sum_{s,d,g,t}\frac{\frac{u_{sdgt}}{n_{dg}}}{F\left(\overline{\overline{t}}_{sdg}\right)}\right) + \beta_2\left(\sum_t \min_d\left\{\sum_{w,g}\frac{\frac{z_{wdgt}}{n_{dg}}}{F(\overline{t}_{wd})}+\sum_{s,g}\frac{\frac{u_{sdgt}}{n_{dg}}}{F\left(\overline{\overline{t}}_{sdg}\right)}\right\}\right). \tag{1}$$

To optimize the efficacy, distress, and balance of the considered DRSC network, a new efficacy-distress measure called service utility and a new balance measure are introduced, which are, respectively, estimated as the ratio of the fraction of fulfilled demand to deprivation cost and the minimum amount of the total service utility among affected areas. Following the lead of Lin et al. (2012), who presented an objective function formulated as the sum of the efficiency and imbalance of the designed DRSC network, the objective function (1) has also been formulated as the weighted sum of the efficacy-distress and balance of the DRSC network. This objective function represents the desire to service the affected areas with the highest possible number of RCs and the least possible deprivation cost in the fairest possible manner (in terms of the amount of distributed RCs and deprivation cost). The first and second expressions of the objective function (1) maximize the utilities of service to affected areas by warehouses and suppliers, respectively. The third expression focuses on maximizing the equity in service by maximizing the minimum amount of total service utility among affected areas

S. T.:

$$\sum_{o} x_{sgot} \leq 1 \forall s \in S, g \in G, t \in T. \tag{2}$$

Constraint (2) ensures that at most one quantity interval can be selected in initial ordering

$$q_{sgot} \geq \underline{l}_{sgo} x_{sgot} \quad \forall s \in S, g \in G, o \in O, t \in T \tag{3}$$

$$q_{sgot} \leq \bar{l}_{sgo} x_{sgot} \quad \forall s \in S, g \in G, o \in O, t \in T. \tag{4}$$

Constraints (3) and (4) guarantee that each initial order belongs to a quantity interval

$$\sum_{t} y_{wt} \leq 1 \forall w \in W. \tag{5}$$

Constraint (5) assures that each warehouse can be established at most once

$$2k_{w\acute{w}t} \leq \sum_{\acute{t}, \acute{t} \leq t} y_{w\acute{t}} + \sum_{\acute{t}, \acute{t} \leq t} y_{\acute{w}\acute{t}} \forall w, \acute{w} \in W, t \in T. \tag{6}$$

Constraint (6) implies that RCs can be transferred between two warehouses at pre-disaster if both respective warehouses are available

$$k_{w\acute{w}t} + k_{\acute{w}wt} \leq 1 \forall w, \acute{w} \in W, t \in T. \tag{7}$$

Constraint (7) indicates one-way relationships among warehouses since if an RC is transferred from warehouse w to warehouse $\acute{w}$ at a period, returning it from warehouse $\acute{w}$ to warehouse w in the same period would be pointless

$$\sum_{\acute{w}} h_{w\acute{w}gat} \leq in_{wg(a-1)(t-1)} \forall w \in W, g \in G, a \in A, 0 < a < \min\left(\acute{a}_g, t\right), t \in T. \tag{8}$$

Constraint (8) denotes the maximum capacity for transferring the RC from one warehouse to other warehouses

$$\sum_{g,a} h_{w\acute{w}gat} \leq M k_{w\acute{w}t} \forall w, \acute{w} \in W, t \in T. \tag{9}$$

Constraint (9) ensures that no RCs will be moved between two warehouses if there is no link between them

$$in_{wgat} = \acute{q}_{wgt} \forall w \in W, g \in G, t \in T, a = 0 \tag{10}$$

$$in_{wgat} = in_{wg(a-1)(t-1)} + \sum_{\acute{w}} h_{\acute{w}wgat} - \sum_{\acute{w}} h_{w\acute{w}gat} \forall w \in W, g \in G, t \in T, t > 1, a \in A, 0 < a < \min\left(\acute{a}_g, t\right) \tag{11}$$

$$in_{wgat} = in_{wg(a-1)(t-1)} \forall w \in W, g \in G, t \in T, t > 1, a \in A, a < t, a = \acute{a}_g. \tag{12}$$

Constraints (10)–(12) express the inventory balance of RCs at each warehouse for ages 0, $0 < a < \acute{a}_g$, and $\acute{a}_g$, respectively

$$\sum_{a, a < \acute{a}_g} in_{wgat} \leq c_{wg} \sum_{\acute{t}, \acute{t} \leq t} y_{wt} \forall w \in W, g \in G, t \in T. \tag{13}$$

Constraint (13) considers the storage capacity of each warehouse for each RC

$$\sum_{a, a \geq \acute{a}_g} in_{wgat} = r_{wgt} \forall w \in W, g \in G, t \in T. \tag{14}$$

Since disaster occurrence time is unknown and the disaster may occur at any time of the considered PTH, constraint (14) determines the number of RCs that should be sent back to the suppliers from the warehouses before expiration

$$\sum_{w, \acute{t}, \acute{t} \leq t} \acute{q}_{wg\acute{t}} = \sum_{w, a < \acute{a}_g} in_{wgat} + \sum_{w, \acute{t}, \acute{t} \leq t} r_{wgt} \forall g \in G, t \in T. \tag{15}$$

Constraint (15) maintains a balance among the total quantity of RCs dispatched from the suppliers to warehouses, the total quantity of RCs returned from warehouses to suppliers, and the total quantity of RCs at warehouses at the start of each period

$$\sum_{a, a < \acute{a}_g} in_{wgat} = \acute{q}_{wgt} + \sum_{\acute{w}, a} h_{\acute{w}wgat} + \sum_{a, a < \acute{a}_g} in_{wg(a-1)(t-1)} - \sum_{\acute{w}, a} h_{w\acute{w}gat} \forall w \in W, g \in G, t \in T, t > 1 \tag{16}$$

$$\sum_{a,a<\acute{a}_g} in_{wgat} = \acute{q}_{wgt} + \sum_{\acute{w},a} h_{\acute{w}wgat} - \sum_{\acute{w},a} h_{w\acute{w}gat} \forall w \in W, g \in G, t \in T, t = 1. \tag{17}$$

Constraints (16) and (17) represent the total inventory at the beginning of the period

$$\sum_{w} \acute{q}_{wgt} = \sum_{s,o} q_{sgot} \forall g \in G, t \in T. \tag{18}$$

Constraint (18) shows the pre-disaster distribution of RCs purchased from suppliers among warehouses

$$\sum_{d} u_{sdgt} \leq \sum_{o} \overline{\mu}_{sgo} q_{sgot} \forall s \in S, g \in G, t \in T. \tag{19}$$

Constraint (19) guarantees that the total quantity of the RCs dispatched from the supplier to affected areas in the post-disaster (secondary order) does not exceed the quantity agreed in the contract

$$\sum_{w} z_{wdgt} + \sum_{s} u_{sdgt} \leq n_{dg} \forall d \in D, g \in G, t \in T. \tag{20}$$

Constraint (20) states that the total delivered amount of the RC to the affected area cannot exceed its demand

$$\sum_{d} z_{wdgt} \leq \sum_{a,a<\acute{a}_g} \rho_{wg} in_{wgat} \forall w \in W, g \in G, t \in T. \tag{21}$$

Constraint (21) confirms that the total amount of the RC dispatched from the warehouse after the disaster cannot exceed its usable inventory

$$\sum_{w,p} \alpha_{wp} ec_{wt} y_{wt} (1+i)^{lp-tp_{wp}} + \overline{v}_t = \left(\overline{b}_t + \overline{v}_{t-1}\right)(1+i)^{lp} \forall t \in T. \tag{22}$$

Constraint (22) is the budget limitation for establishing warehouses by taking into account the time value of money. This constraint states that the sum of the future value of establishment costs must not be more than the future value of the existing budget

$$\begin{aligned} &\sum_{s,g,o,p} \acute{\alpha}_{sgop} pc_{sgot} q_{sgot} (1+i)^{lp-t\acute{p}_{sgop}} + \overline{\overline{v}}_t = \left(\overline{\overline{b}}_t + \overline{\overline{v}}_{t-1}\right)(1+i)^{lp} \\ &+ \sum_{s,g,o,p,\acute{t}=t-\acute{a}_g|t\rangle\acute{a}_g} \acute{\alpha}_{sgop} \left(\overline{\tau}_{sgo} pc_{sgot} \underline{\mu}_{sgo} q_{sgo\acute{t}} + \underline{\tau}_{sgo} pc_{sgot} \left(1 - \underline{\mu}_{sgo}\right) q_{sgo\acute{t}}\right) \\ &(1 + q_{sgo\acute{t}})(1+i)^{lp-t\acute{p}_{sgop}} \forall t \in T. \end{aligned} \tag{23}$$

Constraint (23) shows the budget limitation for procuring required RCs at pre-disaster by taking the time value of money into consideration. This constraint expresses that the sum of the future value of purchasing costs must not exceed the sum of the future value of the existing budget and the future value of sale incomes of returned RCs

$$\overline{v}_0, \overline{\overline{v}}_0, k_{w\acute{w}1}, k_{wwt} = 0 \quad \forall w, \acute{w} \in W, t \in T \tag{24}$$

$$y_{wt}, x_{sgot}, k_{w\acute{w}t} \in \{0,1\} \quad \forall w, \acute{w} \in W,\ s \in S, g \in G, o \in O, t \in T \tag{25}$$

$$q_{sgot}, \acute{q}_{wgt}, in_{wgat}, r_{wgt}, h_{\acute{w}wgat}, z_{wdgt},\ u_{sdgt}, \overline{v}_t, \acute{v}_t \geq 0 \ \forall d \in D, w, \acute{w} \in W, s \in S, g \in G, o \in O, t \in T. \tag{26}$$

Constraints (24)–(26) indicate the type of decision variables.

The objective function (1) is non-linear, and we linearize it by utilizing the following relations. In particular, we assume that $\delta_t = \min_d \{\sum_{w,g} \frac{\frac{z_{wdgt}}{n_{dg}}}{F(\overline{t}_{wd})} + \sum_{s,g} \frac{\frac{u_{sdgt}}{n_{dg}}}{F\left(\overline{\overline{t}}_{sdg}\right)}\}$. Therefore, the objective function (1) is changed to Eq. (27), and constraint (28) is added to the model. Constraint (28) ensures that the auxiliary variable δ_t is the minimum value among the total service utility values at period t

$$\textbf{Max } Z = \beta_1 \left(\sum_{w,d,g,t} \frac{\frac{z_{wdgt}}{n_{dg}}}{F(\overline{t}_{wd})} + \sum_{s,d,g,t} \frac{\frac{u_{sdgt}}{n_{dg}}}{F\left(\overline{\overline{t}}_{sdg}\right)} \right) + \beta_2 \left(\sum_{t} \delta_t \right) \tag{27}$$

$$\sum_{w,g} \frac{\frac{z_{wdgt}}{n_{dg}}}{F(\overline{t}_{wd})} + \sum_{s,g} \frac{\frac{u_{sdgt}}{n_{dg}}}{F\left(\overline{\overline{t}}_{sdg}\right)} \geq \delta_t \forall d \in D, t \in T. \tag{28}$$

4 Model implementation and results' analyses

In this section, we report the results of the computational tests to demonstrate the model's applicability and validity. The models are solved via IBM ILOG CPLEX 12.10 running on a laptop with Intel Core i3 2.53 GHz CPU and 2 GB of RAM. In the following, we introduce a set of test problems, and a real-world real case study followed by various sensitivity analyses.

4.1 Test problems

To investigate the computational complexity of the proposed model, five test problems are randomly generated based on real-world situations and CPLEX is run with a time limit of 36,000s. The results are provided in Table 2. Based on the results, it can be concluded that (1) CPLEX is able to achieve the optimal solution for the small- and medium-sized problem, (2) in large dimensions, the

Table 2 Computational complexity evaluation of the model

Problem	Size |S| ×|W| ×|D| ×|G|× |A| ×|T| ×|O| ×|P|	Number of constraints (equality constraints)	Number of variables (binary variables)	Z[a]	Time (s)	Gap%	Number of iterations	Number of cuts
P1	|3| ×|6| ×|3| ×|2| ×|2| ×|3| ×|2| ×|2|	677 (164)	1197 (162)	2.274	0.2	0	623	44
P2	|4| ×|9| ×|6| ×|2| ×|2| ×|4| ×|2| ×|2|	1667 (332)	3428 (424)	8.694	0.66	0	1381	63
P3	|5| ×|12| ×|12| ×|3| ×|3| ×|6| ×|3| ×|3|	5294 (1124)	16,830 (1206)	41.481	248.34	0	543,589	645
P4	|6| ×|18| ×|15| ×|3| ×|4| ×|8| ×|3| ×|3|	13,362 (2550)	54,168 (3168)	70.948	36,000	0.85	13,889,276	4616
P5	|10| ×|25| ×|20| ×|6| ×|6| ×|11| ×|4| ×|4|	39,591 (11,856)	294,283 (8338)	322.391	36,000	1.45	5,304,820	9016

The best feasible value of the objective function achieved within 36,000 s

software is not capable of solving the problem in 36,000s but can achieve a near-optimal solution, and (3) the computational complexity of the problem increases with the increase in its variables and constraints, especially binary variables and equality constraints; as a result, the computation time, gap, and number of iterations and applied cuts increase.

4.2 Case study

Iran is recognized for being one of the world's most seismically active countries, as it is traversed by numerous major faults and has been hit by plenty of devastating earthquakes in recent decades, resulting in numerous fatalities and huge financial losses. Figure 7 depicts the earthquakes with a magnitude greater than four that occurred in Iran from 1900 to 2020 (IIEES, www.iiees.ac.ir). Iran's second most populous city is Mashhad, with a population of over 3 million people. This city is Iran's most important religious tourism hub, with over 20 million tourists visiting each year, resulting in increased population density. The city is also one of the most important and fundamental cities of Iran due to the existence of some critical factories and industries, as well as its vital and critical role in the development and expansion of the country's eastern provinces. The existence of unfavorable urban conditions, such as the lack of strength in buildings, and old and worn textures in different areas of the city, which have little stability against earthquakes, has intensified the vulnerability of its different areas [see Figure 8 (Hafezi-Moghaddas 2007)]. Therefore, it can be stated that an earthquake in this metropolis may result in tremendous and irreversible human and financial losses. Hence, earthquake disaster management in Mashhad is of particular importance.

The possibility of a high-intensity earthquake in Mashhad is considered in this case study. The data and information are gathered from reliable and trustworthy sources provided based on Mashhad's actual conditions, via interviews with some disaster management experts,[10] and from case studies conducted in Iran. The considered hypotheses and data are as follows:

- Mashhad is divided into 13 districts, which are referred to as affected areas. To locate the warehouses, one location is nominated in each district based on criteria, such as seismic hazard, distance from active faults, and vulnerability of the network of passages. The affected areas and candidate locations for warehouses are shown in Fig. 9.
- Three types of RCs, namely, canned tuna, canned beans, and drinking water, are needed to be stored in available warehouses. Three liters of drinking water, one can of tuna, and one can of beans are a person's daily requirement for drinking water and food (Sphere 2018). Therefore, each affected person will require 9 L of drinking water, three cans of tuna, and three cans of beans for the first 72 h of immediate aftermath.
- For each RC type, five reliable suppliers, whose locations are provided in Fig. 9, are recognized. It is worth noting that canned tuna and canned beans are both supplied by the same suppliers.
- The RCs are kept in warehouses in favorable circumstances, and the return time of each RC to its corresponding supplier is agreed upon at 1.5 years.
- The pre-disaster PTH is 3 years, divided into 6 periods of 6 months.
- For each period, Table 5 shows the establishment and procurement budgets.

[10] We conducted oral interviews with three experts from Mashhad's Red Crescent Society, one expert from the Department of Passive Defense of Mashhad's Governorate, and one expert from the Department of Passive Defense of Astan Quds Razavi, who specialize in crisis management and have complete information on the performance and situation of Iran's relief systems. We also conducted oral interviews with three professors of Ferdowsi University of Mashhad, who specialize in earthquakes.

- The 6-month general inflation rate is set at 21% (average 6-month general inflation rates of 2018–2021).
- Throughout the pre-disaster PTH, the budgets are deposited in a bank that calculates profit daily under a nominal annual interest rate of 10%. As a result, the effective daily interest rate is 0.0274%.
- The number of affected people in each area is estimated by multiplying the population size by the predicted damage percentage. The predicted damage percentage is calculated using the common set of weights and data envelopment analysis techniques (DEA-CSW method) for which 16 criteria are considered. In particular, the considered criteria are as follows: (1) health per capita, (2) green space per capita, (3) network of passages per capita, (4) number of fire stations, (5) development stage, (6) percentage of low-durability buildings, (7) age of buildings, (8) population density, (9) horizontal acceleration of faults, (10) soil erosion, (11) slope, (12) proximity to faults, (13) soil liquefaction, (14) area of hazardous applications, (15) traffic service level, and (16) percentage of buildings with more than three floors. According to the experts' opinions, 40% of the inefficiency score obtained from the DEA-CSW method is considered as the predicted damage percentage. Accordingly, the quantity of demand for each RC type is reported in Table 6.
- Table 7 displays the storage capacity of three RC types which are, respectively, 21, 21, and 42% of the population size of the corresponding district and adjacent districts.
- To estimate the construction cost per square meter, the seismic resistance of each district is first evaluated using step-wise weight assessment ratio analysis (SWARA) and simple additive weighting (SAW) methods. In particular, horizontal acceleration of faults, soil erosion, slope, proximity to faults, and soil liquefaction are effective criteria of the proposed method. It is worth noting that the lower the land's seismic resistance, the stronger the building is required, which leads to higher construction costs. Finally, the establishment cost of each warehouse is estimated by considering its seismic resistance and capacity and construction cost per square meter in Mashhad, as shown in Table 3.
- The percentage of possible earthquake damage to each warehouse is estimated using the DEA-CSW method for which eight criteria are considered as follows: (1) network of passages per capita, (2) number of fire stations, (3) horizontal acceleration of faults, (4) soil erosion, (5) slope, (6) proximity to faults, (7) soil liquefaction, and (8) traffic service level. It is worth mentioning that the possible damage percentage accounts for 15% of the inefficiency score obtained from the DEA-CSW technique. Finally, the estimated damage percentage is considered as the percentage of stockpiled conserves that are unusable following the disaster. In addition, this percentage for drinking water is taken into account 3% more than the conserves (see Table 7).
- The unit selling price offered by each supplier and its production capacity are extracted from its website, and the rest of the contract parameters are generated randomly while considering their practical and real-world situations. The results are reported in Table 8.
- Following an earthquake, there may be disruptions in the transportation network due to damage to routes and traffic congestion; as a result, travel times may rise compared to normal conditions. Hence, the post-disaster travel time is calculated by multiplying the normal travel time by the coefficient of disruption in the transport route. The measurement tool on Google Maps is used to determine normal travel times from the suppliers and warehouses to the centers of the affected areas. Also, to estimate the coefficient of disruption in the transport route, according to the real case studies conducted in Iran and experts' opinions, the following approach is utilized:

The districts are first ranked using Fig. 10, created by specialists, and the normalized rank is considered as the percentage of road damage. Then, the coefficient of disruption in the transportation network of each district is estimated as ten times the sum of the percentage of road damage and the percentage of

district damage (the second column of Table 2). Finally, the amount of the coefficient of disruption in the transport route is measured as the average coefficients of disruption in the transportation network of the districts that the route passes through. The results are provided in Tables 9, 10, 11 and 12.

The establishment cost of each warehouse is paid in three installments, namely, 1) 45% of the cost at the beginning of the period, 2) 35% of the cost at 30 days after the beginning of the period, and 3) 20% of the cost at 60 days after the beginning of the period.

β_1 and β_2 are set to 0.5 by performing a sensitivity analysis (see Table 12).

Table 3 Amount of RCs transferred from suppliers to affected areas

Period	Commodity	Supplier	Affected area												
			1	2	3	4	5	6	7	8	9	10	11	12	13
1	Canned tuna	5					105,510		2530						
	Canned beans	5					105,510		7624						
	Drinking water	4												80,360	
2	Canned tuna	1												75,698	
	Canned beans	5				11,755	105,510								
	Drinking water	3										115,826		164,214	
3	Canned tuna	1												73,535	
	Canned beans	5				54,409	72,081								
	Drinking water	3										115,826		164,214	
4	Canned tuna	1											3791	82,107	
		5				54,409	65,591								
	Canned beans	1												13,956	
		5				54,409	85,591								
	Drinking water	3			18,587							2460	116,618	164,214	
5	Canned tuna	3										6283			
		5				54,409	65,591								
	Canned beans	1											18,020	76,317	
		5				68,778	71,222								
	Drinking water	2			155,709							2460	69,366		
		3			115,826									164,214	
6	Canned tuna	1												76,317	
		5				54,409	65,591								
	Canned beans	4											37,979		
		5				54,409	85,591								
	Drinking water	3			153,326							2460		164,214	
		4			54,620										

4.3 Results and analyses

In this section, we provide the results of running the proposed model according to the considered case study, which contains 5892 constraints (including 1220 equality constraints) and 19,434 variables (including 1362 binary variables). IBM ILOG CPLEX 12.10 software finds the optimal solution of the model by applying 876 cuts in 146,830 iterations and 59.45 s. Figure 4 depicts the location and inventory levels of established warehouses, selected suppliers, and the quantity of initial orders placed with them. In addition, in this figure, we provide the relationships between the warehouses (lateral transportation) in each period. For example, in period 3, two warehouses, namely 4 and 6, are established. The inventory of warehouse 1 includes 204,986 cans of tuna, 272,000 cans of beans, and 544,000 bottles of drinking water. In addition, 210,100 cans of tuna, 316,226 cans of beans, and 700,100 bottles of drinking water are purchased from suppliers 1, 5, and 3, respectively. Finally, from each of warehouses 1 and 13, the RCs are sent to both warehouses 4 and 6.

The findings propose that warehouses 2, 3, 8, 11, and 12 cannot be established. In particular, warehouse 12 is further away from the affected areas and has the highest risk of pre-positioned commodities' destruction compared to the

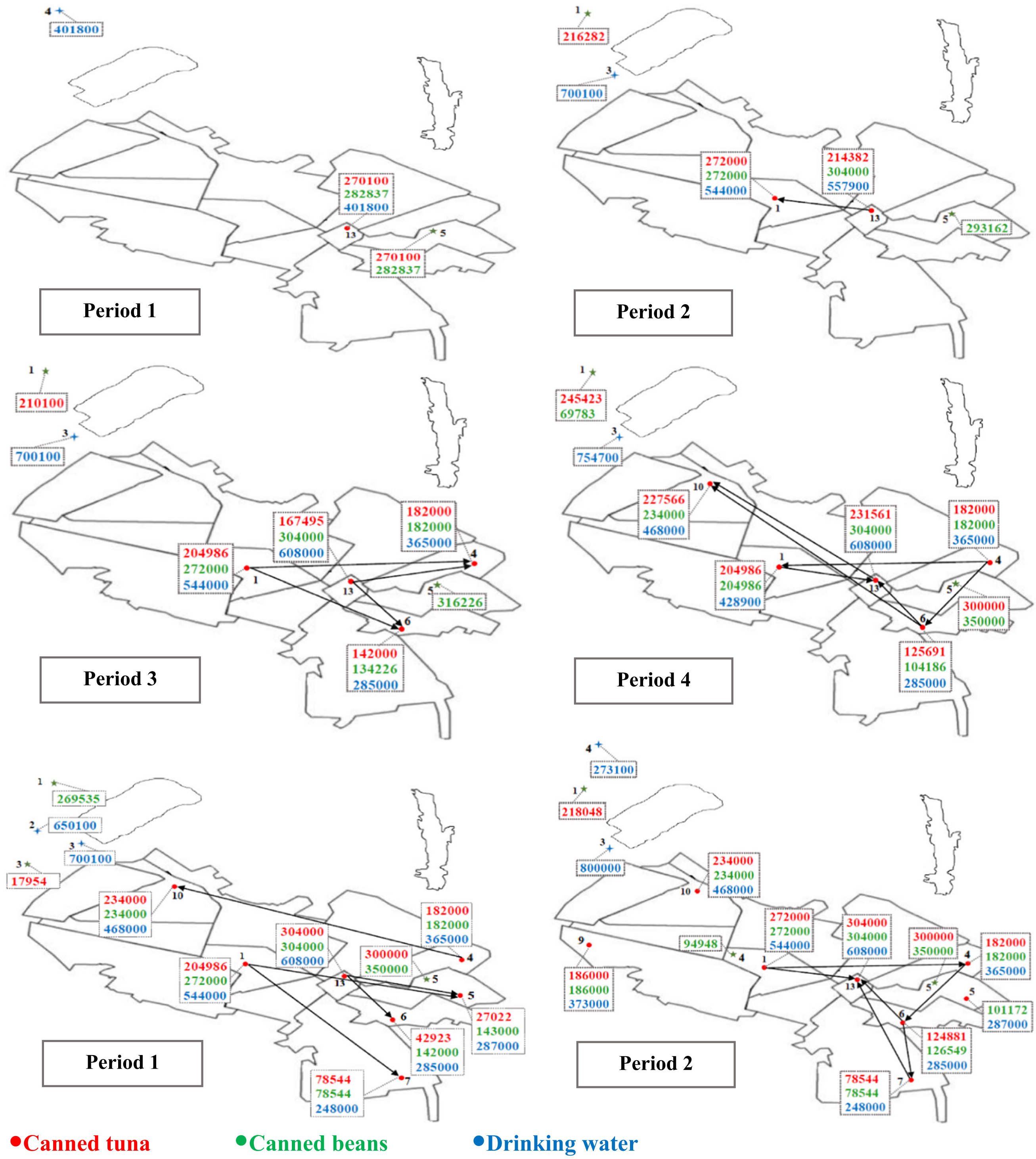

Fig. 4 Established warehouses and their inventory levels (unit), selected suppliers and the number of RCs procured from them (unit), and relationships between warehouses

other warehouses. In addition, warehouses 2, 8, and 11 have the highest establishment costs among available warehouses. Finally, warehouse 3 has good storage capacity, but it is far from the affected areas and has deficient safety and high establishment cost. It is worth noting that the constructed warehouses are closer to the railway station and, or airport than the other warehouses, which can enhance responsiveness.

Analyzing the results shows that those warehouses that provide the capacity to store the procured RCs and are closer to the affected areas are established sooner. Warehouses 1 and 13 are, respectively, located at a shorter distance from the affected areas compared to the other selected warehouses. However, warehouse 1 does not have sufficient capacity to store the RCs purchased in period 1. Therefore, the RO decides to establish warehouses 13 and 1 in periods 1 and 2, respectively. In the third period, warehouses 4 and 6 are founded, because they provide the necessary capacity to store the procured RCs and are closer to the affected areas than warehouses 5, 7, 9, and 10. Considering the establishment budget constraint, the RO has two options in period 4, namely, 1) the establishment of warehouse 10, and 2) the establishment of warehouses 5 and 7. Option 2 is not able to provide the required storage capacity, so option 1 is selected. Finally, warehouses 5 and 7 are constructed in the fifth period and warehouse 9 in the sixth period, as warehouse 9 cannot prepare the storage capacity required in period 5 and is farther away from the affected areas than the other selected warehouses.

In the procurement process, the first and fifth suppliers of conserves and the third supplier of water have more cooperation with the RO. In particular, supplier 5 provides a larger amount of canned beans in all periods, as well as canned tuna in all periods except periods 2 and 3. The first supplier provides canned tuna in all periods except periods 1 and 5 and canned beans in periods 4 and 5. In addition, in all periods except period 1, supplied drinking water from the third supplier is more than the other chosen suppliers. Hence, negotiating with these three suppliers and ensuring long-term cooperation can make the contract terms more beneficial to the RO and lead to an increase in supply capacity.

As seen in Fig. 4, to improve the efficacy, distress, and balance of the relief network, no RCs from warehouses 5 and 10 are sent to the other warehouses. At the same time, they receive the RCs from the other warehouses. Furthermore, no RCs are exchanged between warehouse 9 and the other warehouses.

With the aim of maximizing fair service and satisfied demands, as well as minimizing deprivation cost, the procurement and distribution of RCs following the disaster are planned as presented in Tables 3 and 4.

4.4 Model sensitivity analyses

To assess the efficiency and effectiveness of the model, several sensitivity analyses are carried out on some of the critical assumptions, approaches, and parameters, which are explained in the following subsections.

4.4.1 Sensitivity analysis on the multi-period optimization approach

Holguín-Veras et al. (2013) asserted that the inter-temporal effects of HRSC activities could not be considered in single-period optimization models. Accordingly, Moreno et al. (2016) revealed that using a multi-period optimization approach to optimize post-disaster location, inventory, and distribution decisions improves relief performance. Therefore, in this paper, we also claimed that integrating the major decisions, such as location, inventory management, and distribution in a multi-period horizon may improve coordination in the HRSC. To substantiate this claim, a single-period problem is solved iteratively, taking into account the decisions made in previous periods. This approach is conducted for each period t beginning from the first period onward, and details are provided in Fig. 5. Upon solving the single-period model (Model 2) over six periods, the results show that in both optimization approaches, constructed warehouses and their establishment time are identical. In multi-period optimization, the procurement strategy has been set up in such a way that the total RCs stored in warehouses (TCSW)[11] have reduced. At the same time, total post-disaster procurement (TPDP)[12] has increased to such an extent that it has not only offset the decrease in stored RCs but also resulted in an increase in total satisfied demand (TSD).[13] It is worth noting that storing fewer RCs reduces the risk of lost capital due to the devaluation of RCs. Furthermore, the multi-period optimization model improves the total deprivation cost (TDC)[14] and the total equity in service (TES)[15] by better storing and distributing of RCs. Therefore, multi-period optimization has resulted in the further realization of the objective function and, consequently, a higher optimal value for the objective function.

4.4.2 Sensitivity analysis on lateral transportation

Given a limited pre-disaster budget and its gradual injection into the project, pre-disaster lateral transportation can be an efficient and appropriate alternative to improve service, as it helps to make inventory levels more favorable in warehouses that are more suitable. Hence, to investigate the effect of pre-disaster lateral transportation on the proposed problem, it is assumed that RCs cannot be moved

[11] $\sum_{w,g,a<\acute{a}_g,t} in_{wgat}$

[12] $\sum_{s,d,g,t} u_{sdgt}$

[13] $\sum_{w,d,g,t} z_{wdgt} + \sum_{s,d,g,t} u_{sdgt}$

[14] $\sum_{w,d,g,t} F(\bar{t}_{wd}) z_{wdgt} + \sum_{s,d,g,t} F\left(\bar{\bar{t}}_{sdg}\right) u_{sdgt}$(Cotes and Cantillo 2019)

[15] $\sum_t \delta_t$

Table 4 Amount of the RCs transferred from the warehouses to affected areas

Period	Warehouse	Commodity	Affected area												
			1	2	3	4	5	6	7	8	9	10	11	12	13
1	13	Canned tuna						132,594	38,158	64,236					10,803
		Canned beans						132,594	49,748	64,236					10,803
		Drinking water						265,188		66,790					21,606
2	1	Canned tuna	120,252						60,312	64,236					
		Canned beans	120,252						60,312	64,236					
		Drinking water	240,504						104,304	128,472					
	13	Canned tuna					35,028	132,594	16,662						10,803
		Canned beans		116,581				132,594	16,662						10,803
		Drinking water					154,514	265,188	49,644						21,606
3	1	Canned tuna	120,252							64,236					
		Canned beans	120,252							64,236				60,312	
		Drinking water	240,504							128,472	104,304				
	4	Canned tuna				115,196	50,424								
		Canned beans				165,620									
		Drinking water				212,732	108,468								
	6	Canned tuna					55,086		76,974						
		Canned beans		14,427			33,428		76,974						
		Drinking water					102,552		153,948						
	13	Canned tuna		9024				132,594							10,803
		Canned beans		133,243				132,594							10,803
		Drinking water		248,246				265,188							21,606
4	1	Canned tuna	120,252							64,236					
		Canned beans	120,252							64,236					
		Drinking water	240,504							128,472	4167				
	4	Canned tuna				165,620									
		Canned beans				165,620									
		Drinking water				212,732	108,468								
	6	Canned tuna					39,919		76,974						
		Canned beans					19,919		76,974						
		Drinking water					102,552		153,948						
	10	Canned tuna										204,810			
		Canned beans										142,449		68,150	
		Drinking water										407,160			
	13	Canned tuna		67,323				132,594							10,803
		Canned beans		133,243				132,594							10,803
		Drinking water		248,246				265,188							21,606

Table 4 (continued)

Period	Warehouse	Commodity	Affected area												
			1	2	3	4	5	6	7	8	9	10	11	12	13
5	1	Canned tuna	120,252							64,236					
		Canned beans	120,252							64,236	60,312				
		Drinking water	240,504							128,472	104,304				
	4	Canned tuna				165,620									
		Canned beans			14,369	151,251									
		Drinking water				321,200									
	5	Canned tuna										25,941			
		Canned beans											137,280		
		Drinking water											266,910		
	6	Canned tuna					39,919								
		Canned beans		97,772			34,288								
		Drinking water		8274		37,206	211,020								
	7	Canned tuna							76,974						
		Canned beans							76,974						
		Drinking water				81,652			153,948						
	10	Canned tuna										128,493		82,107	
		Canned beans										204,810		5790	
		Drinking water										407,160			
	13	Canned tuna		133,243				132,594							10,803
		Canned beans		133,243				132,594							10,803
		Drinking water		248,246				265,188							21,606
6	1	Canned tuna	120,252							64,236	60,312				
		Canned beans	120,252							64,236	60,312				
		Drinking water	240,504	5246						128,472	99,058				
	4	Canned tuna				165,620									
		Canned beans				165,620									
		Drinking water				321,200									
	5	Canned tuna													
		Canned beans										76,317	20,808		
		Drinking water											266,910		

Table 4 continued

Period	Warehouse	Commodity	Affected area												
			1	2	3	4	5	6	7	8	9	10	11	12	13
6	6	Canned tuna		76,220			39,919								
		Canned beans		97,772			19,919								
		Drinking water		8274		37,206	211,020								
	7	Canned tuna							76,974						
		Canned beans							76,974						
		Drinking water				81,652			153,948						
	9	Canned tuna									8562		168,138		
		Canned beans									67,349		109,350		
		Drinking water									273,794		69,366		
	10	Canned tuna										204,810		5790	
		Canned beans										128,493		82,107	
		Drinking water										407,160			
	13	Canned tuna		133,243				132,594							10,803
		Canned beans		133,243				132,594							10,803
		Drinking water		248,246				265,188							21,606

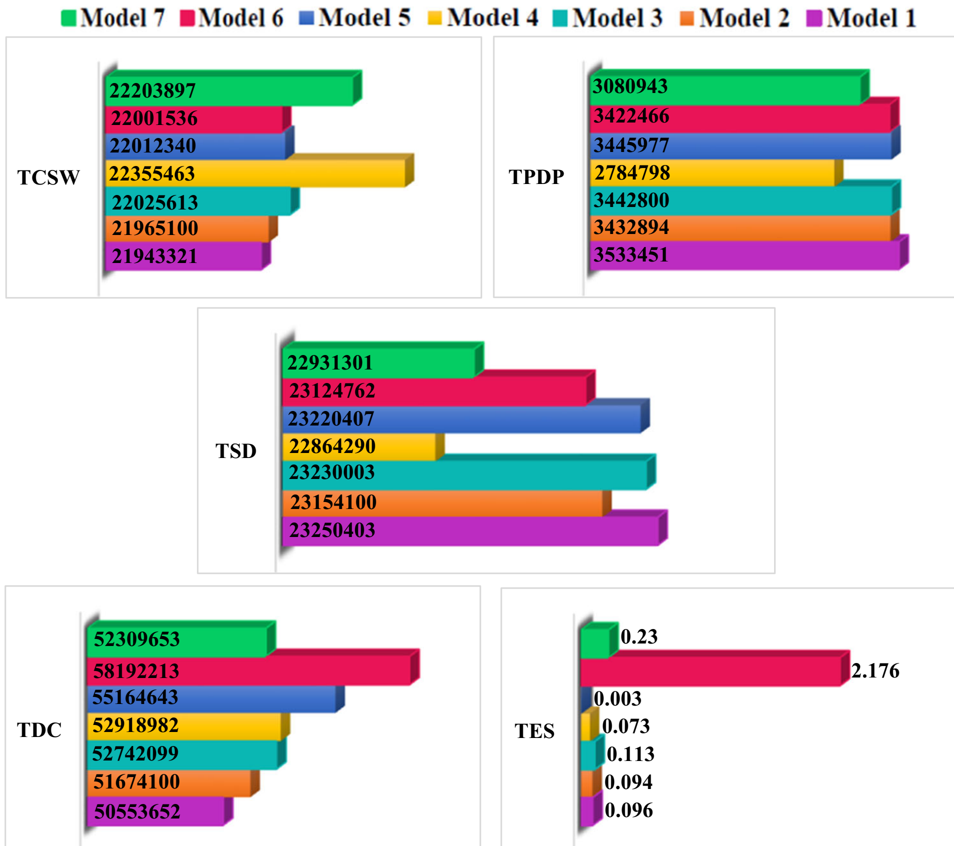

Fig. 5 Effects of some proposed approaches on the problem

between warehouses prior to the disaster (Model 3). Figure 5 illustrates some of the results. In particular, eliminating pre-disaster lateral transportation from the problem does not make any changes to the established warehouses and their establishment time. However, the procurement plan has been adjusted, so that TPDP has significantly decreased. This reduction is so much that the rise in TCSW has not been able to compensate; as a result, TSD has decreased. In addition, the storage and distribution of RCs have not improved, and we have higher values for TDC and TES. Accordingly, the objective function has been realized less, and its optimal value has been reduced. Noteworthy, it is observed that considering post-disaster lateral transportation in the model has only affected how to distribute the RCs in the post-disaster, so that TDC has considerably increased due to some indirect deliveries of the RCs to the affected areas, which have resulted in a dramatic increase in response time. In conclusion, we can state that pre-disaster lateral transportation leads to a better performance of our DRSC network.

4.4.3 Sensitivity analysis on the buyback policy

In this section, we investigate the effect of the buyback policy on the performance of the proposed model. In particular, we assume that RCs would not be returned to suppliers at the agreed time but would instead be kept in warehouses for a while (more extended than the time agreed with suppliers and on the verge of expiration) and then removed from warehouses with a specific salvage value (sale mechanism; Model 4). The findings indicate that the policy used to remove near-expiration RCs from warehouses does not affect the opened warehouses and their establishment time. However, since the sale mechanism holds RCs in warehouses for a longer time and considers a salvage value for each RC that is lower than the prices offered by suppliers, fewer RCs have been purchased prior to the disaster, while TCSW has grown (see Fig. 5). In this mechanism, it has been contracted with suppliers, so that a considerable drop in TPDP has occurred, resulting in a fall in TSD despite growing TCSW. Also, the storage and distribution of RCs have been managed so that TDC has raised, but TES has decreased. Therefore, the objective function has been realized at a lower amount.

4.4.4 Sensitivity analysis on the proposed balance measure

Tzeng et al. (2007) demonstrated that the fair distribution of RCs among affected people is ensured by maximizing a balance measure, formulated as the minimum amount of fraction of the total fulfilled demand among all affected areas. Hence, the current study has also optimized equity in service by maximizing a new balance measure, formulated as the minimum amount of the total service utility among all affected areas. Now, to evaluate the influence of the proposed balance measure on the performance of the designed DRSC network, this measure (i.e., the third expression of the objective function) is eliminated (Model 5). It is observed that eliminating this measure from the problem has no effect on the location and establishment scheduling decisions, but it influences the other decisions (see, Fig. 5). The RO contracts with suppliers in such a manner that pre-disaster purchased RCs have grown; as a result, TCSW has increased, while post-disaster purchased RCs (TPDP) have reduced. The fall in TPDP is to such an extent that the increase in TCSW cannot be offset; as a result, TSD has dropped. Furthermore, storage and distribution strategies have not improved, resulting in a higher value for TDC and a lower value for TES. Therefore, like Tzeng et al. (2007), we can also conclude that optimizing the balance measure ensures fair service and more efficient relief.

4.4.5 Sensitivity analysis on the objective function

The objective function of the model has been formulated as the weighted sum of the efficacy distress and balance of the DRSC network. Now, to investigate the efficiency of the weighted sum method, the proposed model is solved using another popular and widely used multi-objective optimization method called the weighted max–min model presented by Lin (2004) (Model 6). The findings are displayed in Fig. 5. It is observed that in periods 5 and 6, warehouses 9 and 3 have been established, respectively, whereas in the other periods, selected warehouses have not changed. Notably, warehouse 3 has been established instead of warehouses 5 and 7. Compared to warehouses 5 and 7, warehouse 3 is further from the affected areas, the railway station, and the airport, and has lower safety and higher establishment cost. Unlike after the disaster, more RCs have been procured in the pre-disaster; as a result, TCSW has increased, and TPDP has decreased. The rise in TCSW has not been able to offset the reduction in TPDP; hence, TSD has reduced. The storage and distribution of RCs have not improved, and we have higher values for TDC and TES. Furthermore, these results have been found within 695.31 s. Thus, the weighted sum method is more efficient than the weighted max–min model in solving the proposed model.

The purpose of the proposed model is to serve victims with the greatest possible amount of RCs and the least possible deprivation cost in the fairest possible way (in terms of the amount of distributed RCs and deprivation cost). As a result, to further fulfill the objective and, at the same time, reduce computational complexities, a new service utility index has been introduced, based on which the purpose has been formulated as a single objective function. In the literature, to achieve the mentioned purpose, the following objective functions have been employed. Functions (29) and (30), respectively, maximize satisfied demands and the minimum fraction of fulfilled demand among all of the affected areas. Functions (31) and (32), respectively, minimize deprivation cost and the maximum fraction of deprivation cost. Functions (30) and (32), respectively, represent fair service in terms of the amount of distributed RCs and deprivation cost considering the balance concept. To investigate the efficiency and efficacy of the proposed service utility index, it is assumed that the purpose of the problem is formulated by the following functions. Hence, the model is transferred into the following multi-objective programming model that can be solved by weighted max–min and weighted sum methods.

Model 7:

$$\textbf{Max } Z_1 = \sum_{w,d,g,t} z_{wdgt} + \sum_{s,d,g,t} u_{sdgt} \tag{29}$$

$$\textbf{Max } Z_2 = \sum_{t} \min_{d} \left\{ \sum_{w,g} \frac{z_{wdgt}}{n_{dg}} + \sum_{s,g} \frac{u_{sdgt}}{n_{dg}} \right\} \tag{30}$$

$$\textbf{Min } Z_3 = \sum_{w,d,g,t} F(\bar{t}_{wd}) z_{wdgt} + \sum_{s,d,g,t} F\left(\bar{\bar{t}}_{sdg}\right) u_{sdgt} \tag{31}$$

$$\textbf{Min } Z_4 = \sum_{t} \max_{d} \left\{ \sum_{w,g} F(\bar{t}_{wd}) \frac{z_{wdgt}}{n_{dg}} + \sum_{s,g} F\left(\bar{\bar{t}}_{sdg}\right) \frac{u_{sdgt}}{n_{dg}} \right\}. \tag{32}$$

S.T.: Constrains (2)–(26)

The results indicate that the weighted max–min model is more efficient than the weighted sum method in solving the above model, as TSCW, TPDP, TSD, TDC, and TES have achieved much better values.

Figure 5 displays some of the outcomes obtained from the weighted max–min model. The findings reveal considerable changes in the problem decisions. Warehouse 3 has been established instead of warehouses 5 and 7. Among the selected warehouses, the nearest warehouse to the affected areas is warehouse 1, followed by warehouses 13, 6, 4, 10, 3, and 9, respectively. Therefore, warehouse 1 has been constructed first, followed by warehouses 4 and 6, and then warehouses 13, 10, 3, and 9, respectively. Warehouses 4 and 6 have been established ahead of warehouse 13, because warehouse 13 lacks the capacity to store items purchased in period 2. Moreover, the purchase strategy has been designed, so that more RCs have been purchased prior to the disaster as opposed to after the disaster. As a result,

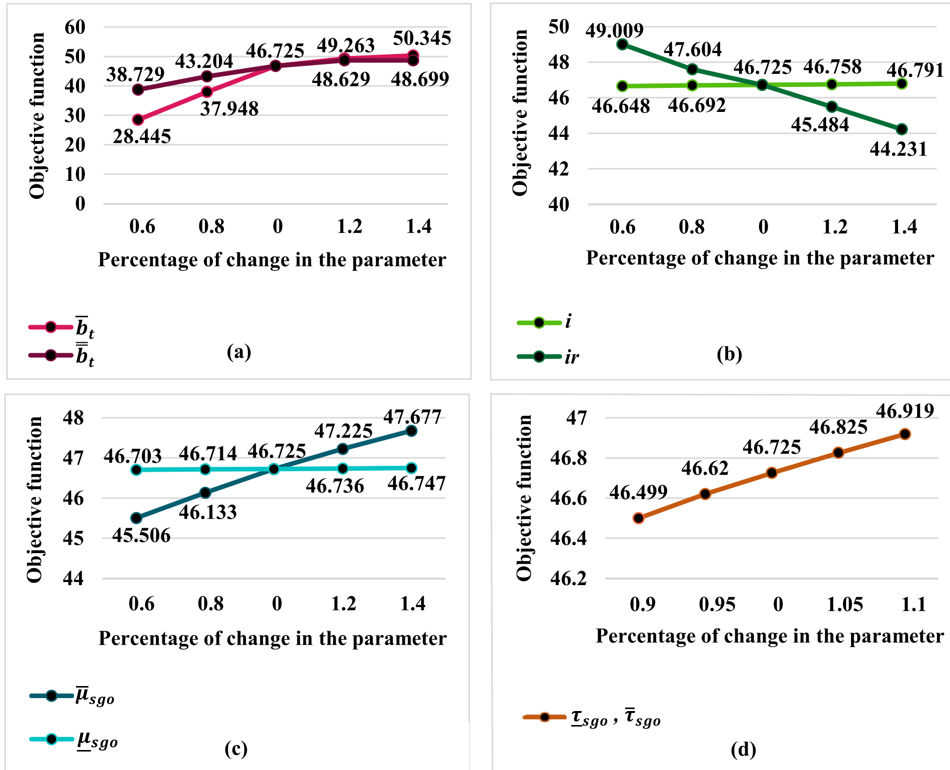

Fig. 6 Effect of varying $\bar{b}_t, \bar{\bar{b}}_t$ (a), i, ir (b), $\underline{\mu}_{sgo}$, $\bar{\mu}_{sgo}$ (c), $\underline{\tau}_{sgo}$, and $\bar{\tau}_{sgo}$ (d) parameters on the objective function

TPDP has dropped, and TCSW has risen. This rise in TCSW is insufficient to compensate for the drop in TPDP; as a result, TSD has dropped. Ample storage at the pre-disaster reduces the supply risk and enhances service efficacy in the aftermath, but raises the risk of capital loss. Finally, the storage and distribution of RCs have been managed, so that TDC and TES have been raised. It is also worth mentioning that these findings have been found within 3240 s. Therefore, it can be concluded that the proposed service utility index results in less computational complexities and the improvement of relief performance.

4.4.6 Sensitivity analyses on $\bar{b}_t, \bar{\bar{b}}_t$, i, ir, $\underline{\tau}_{sgo}$, $\bar{\tau}_{sgo}$, $\underline{\mu}_{sgo}$, and $\bar{\mu}_{sgo}$ parameters

In this section, we perform several tests on some of the main parameters of the model, i.e., $\bar{b}_t, \bar{\bar{b}}_t$, i, ir, $\underline{\tau}_{sgo}$, $\bar{\tau}_{sgo}$, $\underline{\mu}_{sgo}$, and $\bar{\mu}_{sgo}$ to demonstrate how changing model parameters would influence the objective function and findings of the model. These parameters were chosen, because (1) any change in their values can have a considerable effect on the value of the objective function, and (2) their values may vary abruptly throughout the pre-disaster PTH. To do the tests, the variability range for each of these parameters was defined as a 40% fall to a 40% rise in their values. The results of these sensitivity analyses are shown in Fig. 6.

Every change in the purchase budgets ($\bar{\bar{b}}_t$) has not affected the warehouses that can be established. However, there has been little variation in establishment scheduling and a slight decrease in the total establishment cost with the drop in the purchase budgets.

Moreover, the larger the purchase budgets, the more RCs have been procured, which has resulted in more demands being satisfied and, and as a consequence, more efficient service.

Any variation in the effective bank interest rate (i) has had no impact on the selected warehouses and the time of their establishment. Also, by raising the interest rate, the profits allocated to the purchase budgets have increased; as a result, the purchase budgets have grown. Hence, the RO has been able to provide more RCs before the disaster, which has resulted in more satisfied demands and, as a result, more fulfillment of the objective function and a higher optimal value for the objective function.

Revenue from the sale of returned RCs has grown as a consequence of raising the percentages of the return price ($\underline{\tau}_{sgo}$, $\bar{\tau}_{sgo}$) or the percentage of returned RCs with a higher selling price ($\underline{\mu}_{sgo}$). Therefore, the RO has succeeded in procuring more RCs and, as a result, satisfying more demands and providing faster service.

By raising the percentage of secondary orders ($\overline{\mu}_{sgo}$), the RO has been able to purchase more RCs from the suppliers after the disaster, so it has opted to store fewer RCs, which has resulted in a rise in satisfied demands and eventually more efficient responsiveness. It is worth noting that these four contract parameters have not affected warehouse location and establishment scheduling.

5 Conclusion

Natural disasters kill thousands and displace millions of people every year. Therefore, to decrease the damages caused by disasters, proper planning is essential in dealing with these events before their occurrence. One of the most critical actions for disaster planning is the development of DRSC networks. Consequently, this study designed a DRSC network under the perishability of RCs, the gradual injection of the limited pre-disaster budgets, the time value of money, the risk of warehouse disruption, and pre-disaster lateral transportation using a multi-period multi-product mixed-integer non-linear programming model. In each period, the strategic decisions of the problem involved determining the optimal location of warehouses, ordering policy and renewing it, and the flow of RCs throughout the designed network prior to the disaster. The tactical decisions of the problem determined the number of RCs for transferring from pre-selected suppliers and warehouses to affected areas in the post-disaster. The model optimized the efficacy, distress, and balance of the designed network using a new measure called service utility, calculated as the ratio of the fraction of satisfied demand to deprivation cost. A BQFC taking into account the potential of delayed and installment payments, two-part buybacks, as well as quantity-based discounts on its terms integrated with multi-sourcing, was presented to procure the necessary RCs prior to the disaster. A real case study of the plausible earthquake in Mashhad City, along with several sensitivity analyses, was implemented to demonstrate the applicability and performance of the model. The findings revealed that pre-disaster lateral transportation policy, buyback mechanism, multi-period optimization, and the proposed balance and service utility measures improve demand coverage, deprivation cost, and the risk of lost capital and stock. Also, the findings propose some management insights as follows:

- ROs have occasionally struggled or failed in implementing their disaster management policies in reality. One of the major causes contributing to this is a lack of preemptive readiness; hence, the current study aims to reduce this gap. The proposed model simplifies both strategic and tactical decisions for relief managers by merging inventory-related decisions and warehouse location prior to the calamity with relief distribution after the calamity. The structure of the relief network will be more stable as a result of this design approach and affected people will be able to get RCs sooner.
- Applying a contractual strategy between ROs and suppliers (e.g., through a QFC) can help improve HRSC in terms of responsiveness and cost-efficiency. Instead of stockpiling vast amounts of RCs in warehouses, ROs can use the QFC to reserve them. As a result, ROs will not incur huge costs. In addition, ROs can make additional orders and get them promptly following a catastrophe to retain HRSC responsiveness.
- It can be ensured that prior to a calamity, the number of expired RCs at warehouses will be considerably decreased by implementing a return policy for the RCs that are close to their expiration dates. That is, by taking into account the procurement time and shelf life of RCs, as well as the use of a buyback mechanism, relief managers can guarantee a high accessibility level of commodities.
- Due to pre-disaster financial limitations, the RO is only able to allocate a limited budget that will gradually become available over time. This, together with the perishability of RCs, necessitates multi-period decision-making. In this regard, applying the multi-period optimization approach can enhance the responsiveness and cost-efficiency of HRSC.
- According to the results of the sensitivity analysis, pre-disaster budgets, and their investment have a considerable impact on disaster response performance. As a result, financial planning and management can promote service efficiency.
- Under the inability to provide more RCs from supply resources in the pre-disaster phase, pre-disaster lateral transportation is an effective and proper option to more efficiently store procured RCs in warehouses and subsequently improve service.
- In addition to the fact that victims expect that there must be no privileges or priority for certain groups of people, fair service can improve the performance of a DRSC network. Therefore, it is essential to pay attention to equity in service when designing a relief network.
- When striving to simultaneously optimize demand coverage, deprivation cost, and fair service, formulating these objectives as the proposed objective function significantly reduces solution time and can result in more fulfillment of them.

The development of the problem in question can be suggested to other researchers for future inquiries. To this end, the following can be taken into account:

- The random and unpredictable nature of the crisis necessitates crisis management within an uncertain environment. As a result, many of the examined papers used a scenario-based stochastic optimization approach, while other uncertain optimization approaches were overlooked. Besides, given the researchers' identification of disadvantages in the scenario-based stochastic programming approach, presenting an uncertain optimization approach, such as robust optimization, fuzzy optimization, and probabilistic optimization for the problem under examination, can be helpful.

- To provide excellent service levels, processes in an HRSC should be analyzed in general rather than in detail. As a result, decentralized and hierarchical decisions can better achieve the goals of an HRSC. For this purpose, the use of multi-level programming can be beneficial. Nevertheless, very few studies have focused on multi-level optimization problems to date. Therefore, modeling the problem under study in the form of a multi-level optimization model can provide a more realistic relief network; it also allows for observing how decisions made in each part of the network can influence or be influenced by decisions made in other areas.
- In this study, it was assumed that suppliers are reliable and that the disaster would not have a negative impact on suppliers. While there is a possibility of disruption in suppliers. Therefore, using proper resilience tactics is beneficial to deal with this supply risk.
- Considering secondary disasters and the collaboration and coordination of several ROs in a collaborative setting, prioritizing RCs and affected areas, employing an efficient covering location model, and presenting an exact or heuristic or meta-heuristic solution method for larger scale problems are other intriguing possible directions for further studies.

This study, like other studies, was not without limitations. The lack of sufficient cooperation of some ROs and researchers in accessing some information and the non-existence of an official database for some of the required data, which resulted in the experts' estimations were asked to help, were among the most important limitations of the current research.

Appendix 1: Data of the case study

Tables 5, 6, 7, 8, 9, 10, 11, 12 and Figs. 7, 8, 9, 10 present the data and information of the case study conducted in the present research.

As can be seen in Table 12, by increasing β_1 or decreasing β_2, the optimal values of TSU and TES follow

Table 5 Budgets for the establishment and procurement of relief supplies) million tomans(

Period	1	2	3	4	5	6
Establishment budget	4000	4000	5000	5000	6500	6500
Procurement budget	7500	9500	11,500	14,500	18,500	21,500

Table 6 Predicted damage percentage (%), population size, number of affected people, and demand (unit)

Affected area	Damage percentage	Population size	Number of affected people	Demand of canned tuna	Demand of canned beans	Demand of drinking water
1	24	167,013	40,084	120,252	120,252	240,504
2	15	513,365	77,005	231,015	231,015	462,030
3	29	417,950	121,206	363,618	363,618	727,236
4	28	261,938	73,343	220,029	220,029	440,058
5	20	175,849	35,170	105,510	105,510	211,020
6	19	232,616	44,198	132,594	132,594	265,188
7	10	256,575	25,658	76,974	76,974	153,948
8	24	89,216	21,412	64,236	64,236	128,472
9	19	327,061	62,142	186,426	186,426	372,852
10	23	296,823	68,270	204,810	204,810	409,620
11	28	200,161	56,046	168,138	168,138	336,276
12	26	105,263	27,369	82,107	82,107	164,214
13	26	13,849	3601	10,803	10,803	21,606

Table 7 Storage capacity (unit), establishment cost (million tomans), and percentage of unusable inventory (%)

Warehouse	Storage capacity			Establishment cost	Percentage of unusable inventory		
	Canned tuna	Canned beans	Drinking water		Canned tuna	Canned beans	Drinking water
1	272,000	272,000	544,000	3391.2	10	10	13
2	335,000	335,000	670,000	3942.3	6	6	9
3	272,000	272,000	544,000	3202.8	9	9	12
4	182,000	182,000	365,000	1768.2	9	9	12
5	143,000	143,000	287,000	1390.2	4	4	7
6	142,000	142,000	285,000	1480.5	7	7	10
7	124,000	124,000	248,000	1808.1	2	2	5
8	267,000	267,000	534,000	4072.2	4	4	7
9	186,000	186,000	373,000	2456.7	5	5	8
10	234,000	234,000	468,000	3240	10	10	13
11	338,000	338,000	676,000	4680	8	8	11
12	195,000	195,000	390,000	2700	11	11	14
13	304,000	304,000	608,000	3159	9	9	12

Table 8 Contract parameters for every supplier-provided quantity interval

	Canned tuna			Canned beans			Drinking water		
	Interval 1	Interval 2	Interval 3	Interval 1	Interval 2	Interval 3	Interval 1	Interval 2	Interval 3
Supplier 1									
$\underline{l}$(unit)	0	180,000	210,000	0	180,000	250,000	0	350,000	550,000
$\bar{l}$(unit)	180,000	210,000	250,000	180,000	250,000	300,000	350,000	550,000	680,000
pc_1 (tomans)	14,200	13,700	13,200	11,000	10,700	10,200	2000	2000	2000
$\bar{\mu}$(%)	20	35	35	20	35	35	10	25	25
$\underline{\mu}$(%)	30	30	30	20	30	40	25	30	35
$\bar{\tau}$(%)	65	69	75	64	67	73	65	70	75
$\underline{\tau}$(%)	60	63	68	60	60	65	60	65	70
$\acute{\alpha}$(%)	100	[80,20]	[65,35]	[85, 15]	[70,30]	[60,40]	100	[75,15,10]	[60,15,25]
$t\acute{p}$(day)	0	[35,45]	[45,60]	[0,35]	[0,35]	[30,45]	0	[0,35,45]	[35,45,60]
Supplier 2									
$\underline{l}$(unit)	0	200,000	240,000	0	200,000	260,000	0	450,000	650,000
$\bar{l}$(unit)	200,000	240,000	270,000	200,000	260,000	320,000	450,000	650,000	800,000
pc_1 (tomans)	14,500	14,500	13,500	11,300	11,300	10,800	2200	2000	1700
$\bar{\mu}$(%)	15	20	28	14	20	27	12	25	35
$\underline{\mu}$(%)	25	35	35	20	25	35	30	40	40
$\bar{\tau}$(%)	65	69	74	68	71	75	68	68	71
$\underline{\tau}$(%)	60	65	65	65	68	70	65	65	65
$\acute{\alpha}$(%)	100	100	[70,30]	[80,20]	[70,30]	[60,40]	[70,15,15]	[70, 15, 15]	[60,20,20]
$t\acute{p}$(day)	0	35	[35,55]	[0,30]	[30,50]	[35,60]	[0,20,35]	[20,30,45]	[25,40,60]
Supplier 3									
$\underline{l}$(unit)	0	170,000	250,000	0	200,000	280,000	0	600,000	700,000
$\bar{l}$(unit)	170,000	250,000	290,000	200,000	280,000	340,000	600,000	700,000	800,000
pc_1 (tomans)	14,900	14,200	14,200	12,000	11,500	11,000	2500	2300	1900
$\bar{\mu}$(%)	35	35	35	12	15	38	30	40	40
$\underline{\mu}$(%)	30	30	40	25	35	50	30	40	50
$\bar{\tau}$(%)	70	70	77	65	70	75	72	77	77

Table 8 (continued)

	Canned tuna			Canned beans			Drinking water		
	Interval 1	Interval 2	Interval 3	Interval 1	Interval 2	Interval 3	Interval 1	Interval 2	Interval 3
$\underline{\tau}$(%)	65	65	70	60	65	70	66	71	71
$\acute{\alpha}$(%)	100	100	[75,25]	[80,10,10]	[70,30]	[60,20,20]	100	100	[60,25,15]
$\acute{tp}$(day)	30	40	[45,60]	[0,20,35]	[25,40]	[35,45,55]	0	0	[25,35,45]
Supplier 4									
$\underline{l}$(unit)	0	210,000	260,000	0	250,000	300,000	0	400,000	500,000
$\bar{l}$(unit)	210,000	260,000	300,000	250,000	300,000	350,000	400,000	500,000	600,000
pc_1 (tomans)	15,300	14,800	13,800	11,700	11,700	11,700	1900	1600	1600
$\overline{\mu}$(%)	23	32	40	40	40	40	20	20	20
$\underline{\mu}$(%)	25	35	50	30	40	50	20	25	30
$\overline{\tau}$(%)	68	76	76	66	72	78	65	70	70
$\underline{\tau}$(%)	60	70	70	62	67	72	60	65	65
$\acute{\alpha}$(%)	100	[70,20,10]	[60,40]	[85,15]	[80,20]	[65,35]	100	100	[75,25]
$\acute{tp}$(day)	20	[20,30,40]	[35,50]	[0,25]	[20,35]	[35,45]	0	25	[25,45]
Supplier 5									
$\underline{l}$(unit)	0	220,000	270,000	0	200,000	280,000	0	550,000	650,000
$\bar{l}$(unit)	220,000	270,000	300,000	200,000	280,000	350,000	550,000	650,000	730,000
pc_1 (tomans)	15,300	15,300	15,300	11,000	10,500	10,000	2000	2000	1700
$\overline{\mu}$(%)	25	30	40	27	32	40	10	24	35
$\underline{\mu}$(%)	30	40	50	30	40	40	20	20	40
$\overline{\tau}$(%)	69	73	78	66	69	72	66	70	74
$\underline{\tau}$(%)	64	68	73	63	66	69	62	66	70
$\acute{\alpha}$(%)	100	[70,15,15]	[75,25]	[60,15,25]	[60,15,25]	[50,50]	100	100	[65,35]
$\acute{tp}$(day)	20	[20,35,50]	[50,60]	[15,25,35]	[25,35,45]	[45,60]	30	40	[35,60]

Table 9 Coefficient of disruption in transport route, and normal and post-earthquake travel time (in minutes) between the warehouses and the centers of the affected areas

	Affected area												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Warehouse 1													
Disruption coefficient	3.5	3	3.3	3.4	3.5	3.5	2.9	3.6	3.4	3.9	4	3.7	3.9
Normal time	1	17	20	23	23	13	20	11	18	17	17	25	13
Post-earthquake time	4	51	66	79	81	46	58	40	62	67	68	93	51
Warehouse 2													
Disruption coefficient	3.3	2.5	3.2	3.3	3.1	3.1	2.8	3.2	3.5	3.2	3.6	3.1	3.4
Normal time	24	34	26	34	34	30	35	31	27	17	23	17	30
Post-earthquake time	80	85	84	113	106	93	98	100	95	55	83	53	102
Warehouse 3													
Disruption coefficient	3.3	3.2	3.8	3.7	3.3	3.2	2.9	3.9	3.3	3.4	3.6	3.3	4.1
Normal time	31	28	17	29	34	24	38	34	41	28	41	57	30
Post-earthquake time	103	90	65	108	113	77	111	133	136	96	148	189	123
Warehouse 4													
Disruption coefficient	3.4	3.3	3.7	3.5	3.1	3	2.6	3.8	3.3	3.4	3.4	3.4	3.9
Normal time	34	26	16	5	10	23	22	31	36	23	41	34	23

Table 9 (continued)

	Affected area												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Post-earthquake time	116	86	60	18	31	69	58	118	119	79	140	116	90
Warehouse 5													
Disruption coefficient	3.5	3.1	3.3	3.1	2.6	2.7	2.3	2.6	3.5	3.3	3.7	3.4	3.2
Normal time	36	30	28	39	40	38	55	39	29	18	22	25	36
Post-earthquake time	126	93	93	121	104	103	127	102	102	60	82	85	116
Warehouse 6													
Disruption coefficient	3.5	3.2	3.2	3	2.7	2.7	2.1	2.6	2.9	3.2	3.6	3.4	3.2
Normal time	32	17	28	10	10	22	10	19	48	41	29	50	22
Post-earthquake time	112	55	90	30	27	60	21	50	140	132	105	170	71
Warehouse 7													
Disruption coefficient	2.9	3.2	2.9	2.6	2.3	2.1	1.5	2.6	2.8	3.4	3.3	3.3	2.9
Normal time	38	30	39	18	22	35	12	29	36	51	36	43	33
Post-earthquake time	111	96	114	47	51	74	18	76	101	174	119	142	96
Warehouse 8													
Disruption coefficient	3.6	3.2	3.9	3.8	3.5	3.6	3.2	3.6	3.5	3.9	3.9	3.7	4
Normal time	24	15	28	26	26	13	27	18	40	41	36	49	8
Post-earthquake time	87	48	110	99	91	47	87	65	140	160	141	182	32
Warehouse 9													
Disruption coefficient	3.4	3.4	3.3	3.3	3.4	2.9	2.8	3.4	3.2	3.8	3.8	3.6	3.7
Normal time	39	52	54	41	41	46	44	34	20	22	18	21	45
Post-earthquake time	133	177	179	136	140	134	124	116	64	84	69	76	167
Warehouse 10													
Disruption coefficient	3.3	3.2	3.4	3.4	3.3	3.4	3	3.6	3.8	3.8	4.1	3.4	3.6
Normal time	28	36	24	37	37	36	38	31	25	6	18	15	32
Post-earthquake time	93	116	82	126	123	123	114	112	95	23	74	51	116
Warehouse 11													
Disruption coefficient	3.5	3.5	3.6	3.6	3.4	3.8	3.1	3.5	3.8	4.1	4.4	3.8	3.7
Normal time	18	32	29	33	34	27	27	22	17	13	12	24	25
Post-earthquake time	63	112	105	119	116	103	84	77	65	54	53	92	93
Warehouse 12													
Disruption coefficient	3	2.8	3.1	3.2	3.1	3.1	2.9	3.2	3.4	3.4	3.8	3	3.3
Normal time	45	53	53	54	55	48	60	52	51	31	46	39	50
Post-earthquake time	135	149	165	173	171	149	174	167	174	106	175	117	165
Warehouse 13													
Disruption coefficient	3.9	3.6	4.1	3.9	3.5	3.5	2.9	4	3.7	3.6	3.7	3.7	4.3
Normal time	17	8	16	17	18	3	22	16	35	31	33	39	5
Post-earthquake time	67	29	66	67	63	11	64	64	130	112	123	145	22

Table 10 Coefficient of disruption in transport route, and normal and post-earthquake travel time (in minutes) between the suppliers of drinking water and the centers of the affected areas

Affected area	1	2	3	4	5	6	7	8	9	10	11	12	13
Supplier 1													
Disruption coefficient	3	2.5	3.2	3.3	3.1	3	2.9	3.2	3.5	3.2	3.6	3.1	3.5
Normal time	67	74	68	65	67	59	76	66	79	79	76	79	77
Post-earthquake time	201	185	218	215	208	177	221	212	277	253	274	245	270
Supplier 2													
Disruption coefficient	3.7	3.1	3.3	3.3	3.2	3.1	3.3	3.7	3.6	3.4	3.7	3	3.6
Normal time	35	44	34	43	43	40	44	41	38	22	28	30	39
Post-earthquake time	130	137	113	142	138	124	146	152	137	75	104	90	141
Supplier 3													
Disruption coefficient	3.7	3.1	3.3	3.3	3.2	3.1	3.3	3.7	3.6	3.4	3.7	3	3.6
Normal time	30	42	32	41	41	37	43	38	35	21	30	18	36
Post-earthquake time	111	131	106	136	132	115	142	141	126	72	111	54	130
Supplier 4													
Disruption coefficient	3.7	3.1	3.3	3.3	3.2	3.1	3.3	3.7	3.6	3.4	3.7	3	3.6
Normal time	64	65	57	68	65	59	66	63	61	54	61	50	63
Post-earthquake time	237	202	189	225	208	183	218	234	220	184	226	150	227
Supplier 5													
Disruption coefficient	3	2.5	3.2	3.3	3.1	3	2.9	3.2	3.5	3.2	3.6	3.1	3.5
Normal time	66	59	53	62	62	53	61	59	51	44	51	35	58
Post-earthquake time	198	148	170	205	193	159	177	189	179	141	184	109	203

Table 11 Coefficient of disruption in transport route, and normal and post-earthquake travel time (in minutes) between suppliers of conserves and centers of affected areas

Affected area	1	2	3	4	5	6	7	8	9	10	11	12	13
Supplier 1													
Disruption coefficient	3.7	3.1	3.3	3.3	3.2	3.1	3.3	3.7	3.6	3.4	3.7	3	3.6
Normal time	43	51	44	61	53	54	56	48	50	31	39	27	54
Post-earthquake time	160	159	146	202	170	168	185	178	180	106	145	81	195
Supplier 2													
Disruption coefficient	3.7	3.1	3.3	3.3	3.2	3.1	3.3	3.7	3.6	3.4	3.7	3	3.6
Normal time	36	46	32	42	42	41	42	41	36	20	28	27	41
Post-earthquake time	134	143	106	139	135	128	139	152	130	68	104	81	148
Supplier 3													
Disruption coefficient	3.7	3.1	3.3	3.3	3.2	3.1	3.3	3.7	3.6	3.4	3.7	3	3.6
Normal time	38	47	34	44	44	43	45	43	38	22	29	29	45
Post-earthquake time	141	146	113	146	141	134	149	160	137	75	108	87	162
Supplier 4													
Disruption coefficient	3.5	3	3.3	3.3	3.5	3.5	2.9	3.6	3.4	3.9	4	3.7	3.9
Normal time	11	30	40	34	32	26	32	25	36	26	27	43	26
Post-earthquake time	39	90	132	113	112	91	93	90	123	102	108	160	102
Supplier 5													
Disruption coefficient	3.2	3.1	3.3	3.1	2.6	2.7	2.3	3.5	3.4	3.2	3.4	3.2	3.5
Normal time	36	19	16	4	7	22	24	28	49	33	52	46	24
Post-earthquake time	116	59	53	13	19	60	56	98	167	106	177	148	84

Table 12 Sensitivity analysis on β_1 and β_2

(β_1, β_2)	(0,1)	(0.1,0.9)	(0.2,0.8)	(0.3,0.7)	(0.4,0.6)	(0.5,0.5)	(0.6,0.4)	(0.7,0.3)	(0.8,0.2)	(0.9,0.1)	(1,0)
TSU[a]	46.223	85.783	90.946	92.413	92.849	93.354	93.38	93.399	93.406	93.407	93.408
TES[b]	3.556	2.171	1.221	0.755	0.503	0.096	0.066	0.038	0.017	0.010	0.003

[a]Total service utility: $\sum_{w,d,g,t} \frac{\frac{z_{wdgt}}{n_{dg}}}{F(\bar{t}_{wd})} + \sum_{s,d,g,t} \frac{\frac{u_{sdgt}}{n_{dg}}}{F\left(\bar{\bar{t}}_{sdg}\right)}$

[b]Total equity in service: $\sum_t \min_d \{ \sum_{w,g} \frac{\frac{z_{wdgt}}{n_{dg}}}{F(\bar{t}_{wd})} + \sum_{s,g} \frac{\frac{u_{sdgt}}{n_{dg}}}{F\left(\bar{\bar{t}}_{sdg}\right)} \}$.

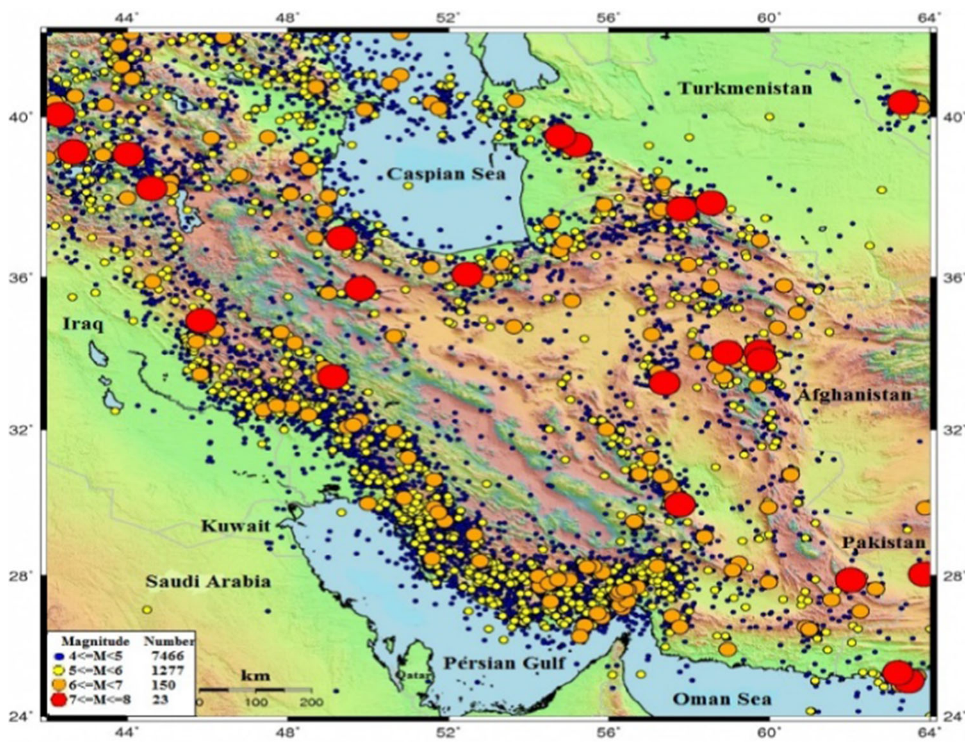

Fig. 7 Seismicity map of Iran from 1900 to 2020 (IIEES, www.iiees.ac.ir)

an incremental trend and a decremental trend, respectively. Notably, TSU has slightly increased, and TES has been realized very little by raising $\beta_1 > 0.5$ or decreasing $\beta_2 < 0.5$. Moreover, by decreasing $\beta_1 < 0.5$ or increasing $\beta_2 > 0.5$, TSU has considerably reduced, while TES has significantly increased. Therefore, considering the higher

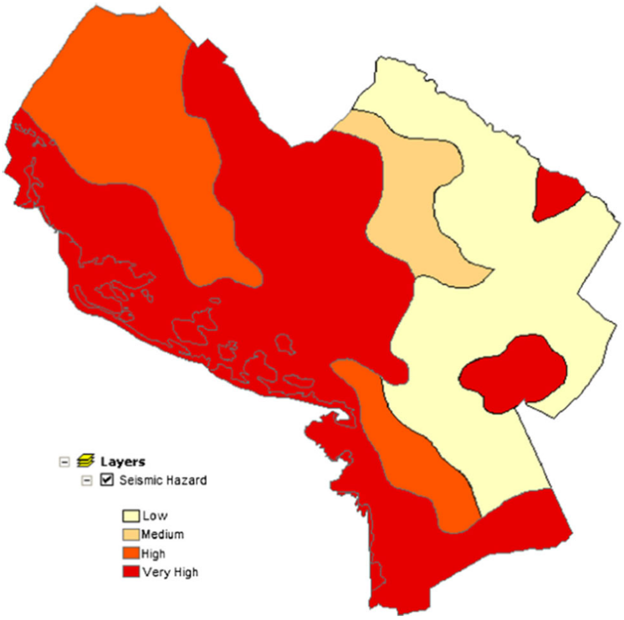

Fig. 8 Seismic hazard level map of different areas of Mashhad (Hafezi-Moghaddas 2007)

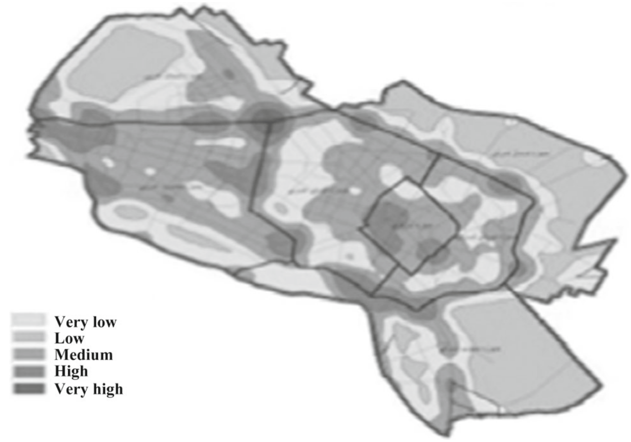

Fig. 10 Vulnerability rating of Mashhad's network of passages

priority of the efficacy-distress measure than the balance measure and the obtained results, β_1 and β_2 are set to 0.5 in this case study.

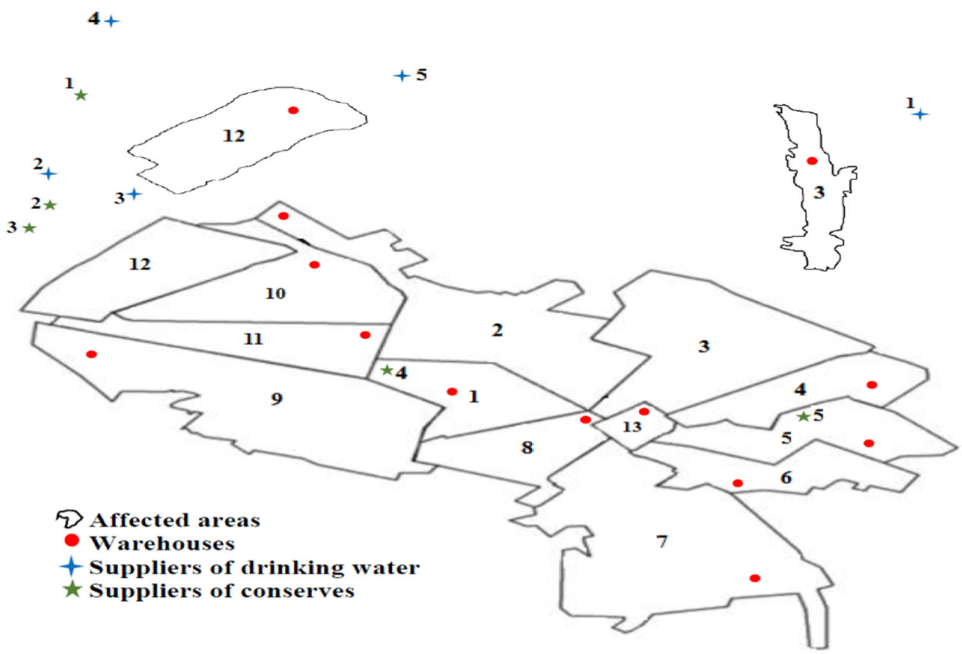

Fig. 9 Locations of affected areas, candidate warehouses, and suppliers

Author contributions LF: conceptualization, methodology, software, writing—original draft, review & editing. MS: conceptualization, methodology, and writing—review & editing. HN: conceptualization, methodology, and writing—review & editing.

Funding The authors have not disclosed any funding.

Data availability The datasets generated during and, or analyzed during the current study and the model's codes in IBM ILOG CPLEX 12.10 software are available in the Github repository, https://github.com/leylafazli/ DRSC.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Abazari SR, Aghsami A, Rabbani M (2021) Prepositioning and distributing relief items in humanitarian logistics with uncertain parameters. Soci-Econ Plan Sci 74:1–17

Aghajani M, Torabi SA, Altay N (2023) Resilient relief supply planning using an integrated procurement-warehousing model under supply disruption. Omega 118:102871

Akbarpour M, Torabi SA, Ghavamifar A (2020) Designing an integrated pharmaceutical relief chain network under demand uncertainty. Transp Res Part E Log Transp Rev 136:1–22

Altay N, Green Iii WG (2006) OR/MS research in disaster operations management. Eur J Oper Res 175:475–493

Aslan E, Çelik M (2019) Pre-positioning of relief items under road/facility vulnerability with concurrent restoration and relief transportation. IISE Trans 51(8):847–868

Bai X, Gao J, Liu Y (2018) Prepositioning emergency supplies under uncertainty: a parametric optimization method. Eng Optim 50(7):1114–1133

Balcik B, Beamon BM (2008) Facility location in humanitarian relief. Int J Log 11(2):101–121

Beamon BM, Balcik B (2008) Performance measurement in humanitarian relief chains. Int J Public Sect Manag 21:4–25

Besiou M, Van Wassenhove LN (2020) Humanitarian operations: a world of opportunity for relevant and impactful research. Manuf Serv Oper Manag 22(1):135–145

Boostani A, Jolai F, Bozorgi-Amiri A (2020) Designing a sustainable humanitarian relief logistics model in pre- and postdisaster management. Int J Sustain Transp 15(8):604–620

Braveman P, Gruskin S (2003) Defining equity in health. J Epidemiol Community Health 57:254–258

Çelik M, Ergun Ö, Johnson B, Keskinocak P, Lorca Á, Pekgün P, Swann J (2012) Humanitarian logistics. In: Mirchandani PB (ed) New directions in informatics, optimization, logistics, and production. INFORMS, Hanover, pp 18–49

Chen D (2020) Prepositioning network design for disaster reliefs: Stochastic models and Ψ-expander models comparison. Comput Ind Eng 140:1–13

Condeixa LD, Leiras A, Oliveira F, Brito ID (2017) Disaster relief supply prepositioning optimization: a risk analysis via shortage mitigation. Int J Disaster Risk Reduct 25:238–247

Cotes N, Cantillo V (2019) Including deprivation costs in facility location models for humanitarian relief logistics. Socioecon Plann Sci 65:89–100

Elçi Ö, Noyan N (2018) Chance-constrained two-stage stochastic programming model for humanitarian relief network design. Transp Res Part B 108:55–83

Erbeyoğulu G, Bilge Ü (2020) A robust disaster preparedness model for effective and fair disaster response. Eur J Oper Res 280(2):479–494

Ergun Ö, Gui L, Heier Stamm JL, Keskinocak P, Swann J (2014) Improving humanitarian operations through technology-enabled collaboration. Product 23(6):1002–1014

Espejo-Díaz JA, Guerrero WJ (2019) A Bi-objective model for the humanitarian aid distribution problem: analyzing the trade-off between shortage and inventory at risk. In: Figueroa-García J, Duarte-González M, Jaramillo-Isaza S, Orjuela-Cañon A, Díaz-Gutierrez Y (eds) 6th Workshop on engineering applications: applied computer sciences in engineering, WEA 2019. Santa Marta, Colombia, pp 752–763

Espejo-Diaz JA, Guerrero WJ (2021) A multiagent approach to solving the dynamic postdisaster relief distribution problem. Oper Manag Res 14:177–193

Falasca M, Zobel CW (2011) A two-stage procurement model for humanitarian relief supply chains. J Human Log Supply Chain Manag 1(2):151–169

Ghasemi P, Amoozad Khalili H, Pourghader Chobar A, Safavi S, Mortaz Hejri F (2022a) A new multiechelon mathematical modeling for pre- and postdisaster blood supply chain: robust optimization approach. Discret Dyn Nat Soc 2022:1–10

Ghasemi P, Goodarzian F, Abraham A (2022b) A new humanitarian relief logistic network for multi-objective optimization under stochastic programming. Appl Intell 52:13729–13762

Ghasemi P, Goodarzian F, Munuzuri J, Abraham A (2022c) A cooperative game theory approach for location-routing-inventory decisions in humanitarian relief chain incorporating stochastic planning. Appl Math Model 10:750–781

Gralla E, Goentzel J, Fine C (2014) Assessing trade-offs among multiple objectives for humanitarian aid delivery using expert preferences. Prod Oper Manag 23:978–989

Gutjahr WJ, Nolz PC (2016) Multicriteria optimization in humanitarian aid. Eur J Oper Res 252(2):351–366

Hafezi-Moghaddas N (2007) Seismic microzonation of the Mashhad city. Technical report. Khorasan-Razavi Housing and Urban Development Organization, Washington, DC

Holguín-Veras J, Pérez N, Jaller M, Van Wassenhove LN, Aros-Vera F (2013) On the appropriate objective function for post-disaster humanitarian logistics models. J Oper Manag 31(5):262–280

Holguín-Veras J, Amaya-Leal J, Cantillo V, Van Wassenhove LN, Aros-Vera F, Jaller M (2016) Econometric estimation of deprivation cost functions: A contingent valuation experiment. J Oper Manag 45:44–56

Hu S, Dong ZS (2019) Supplier selection and pre-positioning strategy in humanitarian relief. Omega 83(C):287–298

Karsu O, Morton A (2015) Inequity averse optimisation in operational research. Eur J Oper Res 245(2):343–359

Kovács G, Spens KM (2007) Humanitarian logistics in disaster relief operations. Int J Phys Distrib Logist Manage 37(2):99–114

Kunz N, Van Wassenhove LN, Besiou M, Hambye C, Kovács G (2017) Relevance of humanitarian logistics research: best practices and way forward. Int J Oper Prod Manag 37(11):1585–1599

Li X, Ramshani M, Huang Y (2018) Cooperative maximal covering models for humanitarian relief chain management. Comput Ind Eng 119:301–308

Li Y, Zhang J, Yu G (2020) A scenario-based hybrid robust and stochastic approach for joint planning of relief logistics and casualty distribution considering secondary disasters. Transp Res Part E Log Transp Rev 141(1):1–21

Lin CC (2004) A weighted max-min model for fuzzy goal programming. Fuzzy Sets Syst 142(3):407–420

Lin YH, Batta R, Rogerson PA, Blatt A, Flanigan M (2012) Location of temporary depots to facilitate relief operations after an earthquake. Socioecon Plann Sci 46:112–123

Maharjan R, Hanaoka S (2017) Warehouse location determination for humanitarian relief distribution in Nepal. Transp Res Proc 25:1151–1163

McLoughlin D (1985) A framework for integrated emergency management. Pub Admin Rev 45:165–172

Moreno A, Alem D, Ferreira D (2016) Heuristic approaches for the multiperiod location-transportation problem with reuse of vehicles in emergency logistics. Comput Oper Res 69:79–96

Mulvey JM, Vanderbei RJ, Zenios SA (1995) Robust optimization of large-scale systems. Oper Res 43(2):264–281

Nagurney A, Masoumi AH, Yu M (2015) An integrated disaster relief supply chain network model with time targets and demand uncertainty. In: Nijkamp P, Rose A, Kourtit K (eds) Regional science matters: studies dedicated to Walter Isard. Springer International Publishing, pp 287–318

Nezhadroshan AM, Fathollahi-Fard AM, Hajiaghaei-Keshteli M (2021) A scenario-based possibilistic-stochastic programming approach to address resilient humanitarian logistics considering travel time and resilience levels of facilities. Int J Syst Sci Oper Log 8:321–347

Noham R, Tzur M (2018) Designing humanitarian supply chains by incorporating actual post-disaster decisions. Eur J Oper Res 265(3):1064–1077

Noyan N, Meraklı M, Küçükyavuz S (2022) Two-stage stochastic programming under multivariate risk constraints with an application to humanitarian relief network design. Math Program 191:7–45

Ransikarbum K, Mason S (2016) Goal programming-based post-disaster decision making for integrated relief distribution and early-stage network restoration. Int J Prod Econ 182:324–341

Rezaei-Malek M, Tavakkoli-Moghaddam R (2014) Robust humanitarian relief logistics network planning. Uncertain Supply Chain Manag 2(2):73–96

Sanci E, Daskin MS (2019) Integrating location and network restoration decisions in relief networks under uncertainty. Eur J Oper Res 279(2):335–350

Sankaranarayanan K, Castañeda JA, Villa S (2018) Future research in humanitarian operations: a behavioral operations perspective. In: Kovács G, Spens K, Moshtari M (eds) The Palgrave handbook of humanitarian logistics and supply chain management. Palgrave Macmillan, London, UK, pp 71–117

Sheikholeslami M, Zarrinpoor N (2023) Designing an integrated humanitarian logistics network for the preparedness and response phases under uncertainty. Socioecon Plan Sci 86:101496

Sphere (2018) Humanitarian charter and minimum standards in humanitarian response, 4th edn. Geneva, Switzerland

Tavana M, Abtahi AR, Di Caprio D, Hashemi R, Yousefi-Zenouz R (2018) An integrated location-inventory-routing humanitarian supply chain network with pre- and post-disaster management considerations. Socioecon Plan Sci 64:21–37

Tomasini R, Van Wassenhove LN (2009) Humanitarian logistics. Palgrave Macmillan, Houndmills

Torabi SA, Shokr I, Tofighi S, Heydari J (2018) Integrated relief pre-positioning and procurement planning in humanitarian supply chains. Transp Res Part E 113:123–146

Tzeng G, Cheng H, Huang T (2007) Multi-objective optimal planning for designing relief delivery systems. Transport Res Part E Log Transport Rev 6:673–686

Wang Q, Nie X (2019) A stochastic programming model for emergency supply planning considering traffic congestion. IISE Trans 51(8):910–920

Wang BC, Li M, Hu Y, Huang L, Lin SM (2020) Optimizing locations and scales of emergency warehouses based on damage scenarios. J Oper Res Soc China 8:437–456

Wang W, Yang K, Yang L, Gao Z (2021a) Two-stage distributionally robust programming based on worst-case mean-CVAR criterion and application to disaster relief management. Transp Res Part E 149:1–22

Wang Y, Dong ZS, Hu S (2021b) A stochastic prepositioning model for distribution of disaster supplies considering lateral transshipment. Socioecon Plan Sci 74:1–10

Zhang J, Li Y, Yu G (2022) Emergency relief network design under ambiguous demands: a distributionally robust optimization approach. Exp Syst Appl 208:118139