https://doi.org/10.1016/j.aei.2020.101223

Multi-modal transportation planning for multi-commodity rebalancing under uncertainty in humanitarian logistics

Xuehong Gao[1,2*], Xuefeng Jin[3], Pai Zheng[4], Can Cui[5]

[1]*Department of Safety Engineering, University of Science and Technology Beijing, Beijing, China*

[2]*Department of Industrial Engineering, Pusan National University, Busan, Republic of Korea*

[3]*Alibaba (China) Co., Ltd, Alibaba Supply Chain Platform (ASCP), Hangzhou, China*

[4]*Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong, China*

[5]*Viewshare Technology Co., Ltd, Beijing, China*

Abstract: Multi-commodity rebalancing plays a critical role before and during the attack of large-scale disasters. In practice, some relief centers can be out of reach from the ground for vehicles due to the road disruption. Accordingly, alternative transportation systems are essential to maximize fairness and minimize the total transportation time, simultaneously. However, little study has reported on this issue for humanitarian logistics. To address it, a bi-objective stochastic optimization model is proposed to rebalance and transport commodities with the multi-modal transportation system. This work first linearizes the model and then applies an adaptive augmented $\mathcal{E}$-constraint method to obtain a number of Pareto-optimal solutions. Furthermore, a case study of an emergency event is carried out, of which the computational results indicate its decision making effectiveness. Lastly, sensitivity analysis on critical parameters is conducted and the trade-off between the objectives is also analyzed to provide valuable managerial insights.

Keywords: Multi-modal transportation; Stochastic programming; Commodity rebalancing; Transportation planning; Humanitarian logistics.

1. Introduction

Large-scale disasters, natural or man-made were occurring more frequently (Ronke 2018), resulting in a great impact on human beings, such as Coronavirus Disease-19 (COVID-19) and 2019 Plague of Locusts from Kenya. Upon these disasters, rapid and effective disaster responses should be conducted to rescue victims and relieving human suffering (Gao et al. 2017; Wang et al. 2017; Gao et al. 2019; Hu et al. 2019; Gao 2020; Pi et al. 2020). Before the occurrence of large-scale disasters, many relief centers have been pre-determined and various commodities are prepared based on the best estimation at peacetime. Because of the unpredictable disasters, the initial commodity preparedness strategy may be not working in a practical situation, such as the unbalanced medical staff and supplies in response to COVID-19. The

* *Corresponding author:gao2016@pnu.edu*

mismatch between supply and demand results in surpluses and shortages at relief centers (Gao and Lee 2018). To save resources, Gao (2020) defined the multi-commodity rebalancing problem among relief centers.

Generally, vehicles are used to transport commodities among relief centers. However, some relief centers are out of reach from the ground due to road disruption and traffic congestion. Besides, the extremely far distance costs too much time of vehicles, which is unacceptable for refugees. Accordingly, some other transportation systems (e.g. helicopters) need to be applied to transport commodities. In this sense, a multi-modal transportation system should be considered. Note that different modes of transportation have different travel distances between the same two facilities.

Also, various uncertainties need to be considered to describe the disastrous situation. It is difficult to know how many commodities should be kept and needed, which makes the supply and demand uncertain. Besides, the road condition is uncertain as the road information cannot be collected accurately because of some unavoidable reasons (e.g. debris removal or second disasters) (Rath et al. 2016). In addition, the practical consideration of road disruption is inevitable after some large-scale disasters, such as an earthquake (Cao et al. 2020). To the best of our knowledge, this multi-commodity rebalancing and transportation (MCRT) problem with uncertain elements and road disruption has never been studied in the previous studies. To address the main concerns of this study, the following questions need to be considered:

(1) How to characterize the fairness in the MCRT problem and transport commodities over the multi-modal transportation system?

(2) How to formulate the model for the MCRT problem with uncertain elements and road disruption?

(3) What are the influences of multi-modal transportation planning on transportation performance compared with single-modal transportation planning?

(4) What are the managerial insights and implications for decision-makers to handle the MCRT problem?

To address the aforementioned questions and research gap, this study focuses on the MCRT problem under uncertainty and road disruption over the multi-modal transportation network with combined distances. The rest of this paper is organized as follows. Section 2 reviews and discusses the previous studies on the main concerns of this study, where the research gap is identified. Section 3 describes the MCRT problem with pre-defined assumptions. To address it, the MCRT problem is further formulated as a proposed bi-objective stochastic mixed-integer nonlinear programming (BOSMINP) model and the corresponding linearization method is developed in Section 4. Section 5 provides the adaptive augmented $\mathcal{E}$-constraint method and the strategy for handling large-sized problems. Furthermore, a case study is provided with the computational results obtained to validate its effectiveness in Section 6. At last, Section 7 concludes this research by providing valuable managerial insights and highlighting future directions.

2. Literature review

This section reviews the literature by discussing several studies on managing the uncertainties, objectives, multi-modal transportation, mathematical programming, and other considerations in humanitarian logistics.

2.1 Uncertainties in humanitarian logistics

Due to the dynamic environment after a large-scale disaster, the collected information is usually uncertain (Kostoulas et al. 2008; Haghi et al. 2017; Gao and Jin 2020; Balcik and Yanıkoğlu 2020). Various uncertain elements need to be considered to improve the reliability of studies in humanitarian logistics. For instance, Rawls and Turnquist (2010) focused on an emergency response pre-positioning strategy for hurricanes or other disaster threats with uncertain demand and transportation network availability. Rottkemper et al. (2012) developed an optimization model under uncertain demand. Cavdur et al. (2016) proposed a two-stage stochastic programming model for the facility allocation problem under demand uncertainty. Song et al. (2018) proposed an optimization model to optimize supply chain operations for rescue kits in disaster reliefs under demand uncertainty.

Besides, the supply is also a non-negligible uncertain factor in humanitarian logistics. Only a limited number of works covered the uncertain supply. Tofighi et al. (2016) designed a two-echelon humanitarian logistics network under the consideration of inherent uncertain supply, demand, and road availability. Haghi et al. (2017) developed a multi-objective programming model that considered uncertain demand, supply, and cost parameters. Gao and Lee (2018) formulated a multi-commodity redistribution problem with uncertain supply, demand, and road availability. Balcik et al. (2019) proposed a stochastic optimization model to design a collaborative prepositioning network with demand and supply uncertainties to strengthen disaster preparedness. Gao (2020) also considered uncertain supply and road availability in rebalancing commodities in disaster response.

2.2 Multiple objectives in humanitarian logistics

Another main feature of disasters is the inherent multiple objectives that need to be achieved simultaneously. Beyond all question, the objective of humanitarian logistics is different from that of business logistics, which aims to maximize the profit or minimize the cost (Li et al. 2018; Yu et al. 2020), whereas humanitarian logistics aims to maximize fairness or minimize the time of response (Huang et al. 2015; Yu et al. 2018; Li et al. 2019; Gao 2020). For instance, Mohammadi et al. (2016) proposed a multi-objective stochastic optimization model to maximize the total expected demand coverage, minimize the total expected cost, and minimize the difference in satisfaction rates between facilities. However, a suitable model should address human suffering or fairness in humanitarian logistics (Holguín-Veras et al. 2013; Haddow et al. 2017; Rodríguez-Espíndola et al. 2018; Cao et al. 2018). In addition, timeliness, a common objective, is also an important goal in humanitarian logistics so that the commodities can be transported as quickly as possible to satisfy the urgent need of refugees.

Since the uneven disaster severities lead to a growing imbalance between the supply and demand (Emanuel et al. 2020), rebalancing and transporting commodities among these relief centers are required right after a disaster with the goals of maximizing fairness and minimizing timeliness. Regarding the fairness measurements, several methods have been proposed in humanitarian logistics. The penalty cost of unmet demand was widely used in previous studies (Lin et al. 2011; Rawls and Turnquist 2010; Moreno et al. 2016; Bai 2016). However, the penalty cost of unmet demand does not guarantee fairness since the commodities cannot be evenly distributed. Besides, the unmet proportion of required resources was also used by Wang and Sun (2018) without considering the priorities. With the priorities of demand points, the weighted proportion of unmet demand was used to measure fairness by Rivera-Royero et al. (2016), seemingly a more reasonable way to measure fairness. As a consequence, the minimization of the weighted proportion of unmet demand is used to measure fairness in this study.

2.3 Multi-modal transportation in humanitarian logistics

In the last decade, multi-modal transportation planning has received insufficient attention because multi-modal transportation planning is a recently emerging research field and so far has not been explored in detail. Multi-modal transportation planning is generally applied in hub-location related problems. Particularly, both Ishfaq and Sox (2011) and Alumur et al. (2012) considered hub-location problems. Meraklı and Yaman (2016) proposed a mathematical model to solve a robust p-hub median problem under demand uncertainty. Yuan and Yu (2018) developed an optimization model to design a multi-modal transportation network.

This study is different from the above studies because the commodity-flow and transit-related decisions are the main concerns of this study rather than the hub location and network design in multi-modal transportation planning. In the practice of disaster response, it usually involves more than one means of transportation, such as road and air. To the best of our knowledge, multi-modal transportation planning has never been studied in the MCRT problem.

2.4 Stochastic programming approach

At the same time, various mathematical programming approaches (Ni et al. 2018; Rodríguez-Espíndola et al. 2018; Cao et al. 2018; Park et al. 2018; Arnette and Zobel 2019; Gao 2019; Zarbakhshnia et al. 2020; Erbeyoğlu and Bilge 2020; Lu et al. 2020; Gillani et al. 2020; Gao and Cao 2020; Jung et al. 2020) have been applied to handle various humanitarian logistics issues so far. To be specific, a single- or multi-objective mixed-integer programming model is usually used to formulate the humanitarian logistics problems without considering uncertainty (Camacho-Vallejo et al. 2015; Gutjahr and Dzubur 2016; Loree and Aros-Vera 2018; Bababeik et al. 2018; Baharmand et al. 2019). With the uncertainty in the humanitarian logistics problems, the single- or multi-objective stochastic mixed-integer programming model is generally applied (Rath et al. 2016; Paul and Zhang 2019; Gao 2020; Gao and Cao 2020). In this sense, it is easily convinced that the stochastic programming approach can be used to solve the humanitarian logistics problem with uncertainty. Given different uncertain elements, different stochastic programming approaches should be developed. As a consequence, this study proposes a specific BOSMINP model incorporating a multi-modal transportation context and several uncertain elements, which makes the proposed mathematical programming model different from the previous ones.

2.5 Summary

In addition to the above discussion, a clear and comprehensive literature review is provided in Table 1. Because this research focuses on the operations and computational research in humanitarian logistics, some international journals that have the highest relevant contributions are searched, such as, Production and Operations Management, European Journal of Operations Research, Transportation Research Part E: Logistics and Transportation Review, Computers & Industrial Engineering, International Journal of Production Economics, Transportation Research Part B: Methodological, and Socio-Economic Planning Sciences.

As shown in Table 1, some literature gaps can be addressed as follows. Firstly, many recent studies have been focused on pre-positioning network design and inventory strategy. However, only a few studies have been conducted to address the commodity rebalancing process in humanitarian logistics. Secondly, multi-modal transportation planning has never been studied in humanitarian logistics. Thirdly, the previous studies scarcely paid attention to the important criterion of fairness in humanitarian logistics. Also, as noted by Gao and Lee (2018), transporting mixed commodities is a great way to improve vehicle utilization, which has also received insufficient attention in the past. Therefore, this work focus on the MCRT problem to rebalance and transport commodities over a multi-modal transportation network with combined distances under uncertain supply, demand, and road availability, which has never been studied before. Besides, a BOSMINP model is proposed to formulate the above problem, which contains two objectives: (i) maximization of the fairness by minimizing the expected total weighted proportion of unmet demand and (ii) minimization of the expected total transportation time. To solve the problem, a linearization method is developed and an adaptive augmented $\mathcal{E}$-constraint method is applied to analyze the conflicting objectives. This study also develops a specific strategy to handle large-sized problems. Finally, a real case study is implemented to validate the proposed model and method. And the key managerial insights and implications are also summarized for decision-makers.

Table 1 Summary of the literature pertaining to the humanitarian logistics operations

Article	Main problem	Uncertainty	Multi-modal transportation	Mixed delivery	Fairness	Objective	Model	Approach
Mete and Zabinsky (2010)	Medical supplies distribution	Demand	No	No	No	Single	MIP	Exact
Bozorgi-Amiri et al. (2013)	Humanitarian relief logistics	Demand, supply, and cost	No	No	No	Multiple	MINP	Exact
Döyen et al. (2012)	Humanitarian relief logistics	Demand and cost	No	No	No	Single	MILP	Heuristic
Davis et al. (2013)	Commodity distribution	Demand, supply, and network	No	No	No	Single	MILP	Exact
Rennemo et al. (2014)	Commodity distribution	Demand, network, and capacity	No	No	Yes	Multiple	MIP	Exact
Camacho-Vallejo et al. (2015)	Aid distribution	None	No	No	No	Multiple	MINP	Exact
Hong et al. (2015)	Pre-disaster relief network design	Demand and transportation capacity	No	No	No	Single	MILP	Exact
Mohammadi et al. (2016)	Commodity pre-position and distribution	Demand, cost, and time	No	No	No	Multiple	MILP	Heuristic
Bai (2016)	Emergency supplies allocation	Demand and path availability	No	No	Yes	Multiple	MINP	Exact
Gutjahr and Dzubur (2016)	Commodity distribution	None	No	No	No	Multiple	MINP	Exact
Tofighi et al. (2016)	Humanitarian logistics network design	Demand, supply, and network	No	No	No	Multiple	MILP	Exact
Rivera-Royero et al. (2016)	Relief supplies distribution	None	No	No	Yes	Single	MIP	Exact and Heuristic
Haghi et al. (2017)	Relief logistics	Demand, cost, and casualty number	No	No	No	Multiple	MINP	Heuristic
Elci and Noyan (2018)	Humanitarian relief network design	Demand and network	No	No	No	Single	MILP	Exact
Gao and Lee (2018)	Commodity redistribution	Demand, supply, and network	No	Yes	No	Multiple	MINP	Exact
Safaei et al. (2018)	Supply distribution relief network design	Demand and supply	No	No	No	Multiple	MINP	Exact
Bababeik et al. (2018)	Location and allocation of relief trains	None	No	No	No	Multiple	ILP	Exact
Loree and Aros-Vera (2018)	Facility location and inventory allocation	None	No	No	No	Single	MINP	Heuristic
Ni et al. (2018)	Pre- positioning emergency inventory	Demand, inventory, road link capacity	No	No	No	Single	MIP	Exact
Mills et al. (2018)	Distribution of patients	State information	No	No	No	Single	IP	Heuristic
Liu et al. (2019)	Relief distribution	Demand and supply	No	No	No	Single	MILP	Exact
Baharmand et al. (2019)	Distribution center location determination	None	No	No	No	Multiple	MILP	Exact
Balcik et al. (2019)	Pre-positioning network design	Demand and supply	No	No	Yes	Single	MILP	Exact
Arnette and Zobel (2019)	Relief asset pre-positioning	None	No	No	Yes	Single	MILP	Exact
Gao (2020)	Commodity rebalancing	Demand and network	No	Yes	Yes	Multiple	MINP	Exact
Erbeyoğlu and Bilge	Humanitarian network design	Demand	No	No	No	Single	MILP	Exact

(2020)								
This study	MCRT	Demand, supply, and network	Yes	Yes	Yes	Multiple	MINP	Exact

3. Problem statement

This section describes the main problem with the following five subsections.

3.1 Transportation network

In addressing the MCRT problem, relief centers have been pre-determined to stock commodities. However, considering the road disruption and traffic chaos due to the disaster, some relief centers are out of reach for vehicles from the ground. In this sense, this research considers two means of transportation (i.e., vehicles and helicopters) to transport commodities. Two simple examples (i.e., I and II) are provided to illustrate the combined routes between two relief centers A and B (see Fig. 1). As shown in Fig. 1(a), two different routes are connecting A and B. These two routes have different travel distances for vehicles and helicopters, where a helicopter usually chooses the straight-line distance between relief centers. As shown in Fig. 1(b), the road connecting A and B is blocked. In this sense, the commodities can only be transported by helicopters between them.

(a) Example I (b) Example II

Fig. 1. Illustrative examples of the combined routes between two relief centers

To illustrate the main concerns of the problem, a multi-modal transportation network with five relief centers (i.e., 1-5) is depicted in Fig. 2, where the relief centers are represented by circles. As shown in Fig. 2, relief centers 3 and 5 are out of reach for vehicles due to some underlying factors, whereas the helicopters can transport commodities between any two relief centers. Then the task is to assign the vehicles and helicopters to transport commodities over the multi-modal transportation network. Noted that the travel distance of vehicles is the length of the road, whereas the travel distance of helicopters approximately equals Euclidean distance between the geographical locations.

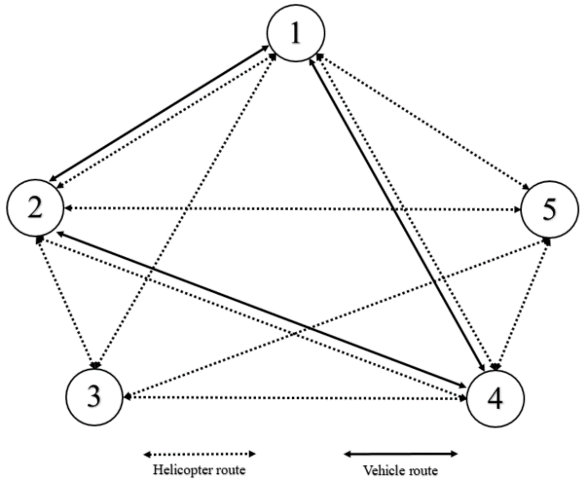


Fig. 2. Multi-modal transportation network of five relief centers

3.2 Uncertainties

In this MCRT problem, the stock levels, supplies, and demand at relief centers should be considered. After comparing the stock levels and demand, the relief centers are generally divided into two groups, namely demand and supply points. Because a disaster creates a highly uncertain environment, the demand and supply are generally uncertain. With the uncertain demand and supply, the relief centers need to be divided into three relief-center categories, which is different from the previous cases. These three relief-center categories also result in a great impact on modeling the mathematical programming model. As mentioned early, the road availability is also uncertain due to various factors. Some roads are slightly damaged or congested, whereas some roads are extremely damaged or blocked. As the road condition cannot be precisely predicted, this study considers the uncertain road condition, which is represented by road availability. Noted that the routes for helicopters are certain.

3.3 Relief-center categories

To illustrate the problem, commodity-type t is considered and each of the relief centers is in charge of distributing commodities to the victims in a certain area. Suppose that a relief center has a stock level S_t and uncertain demand between $\min_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\}$ and $\max_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\}$. After comparing S_t with uncertain demand, this relief center possibly belongs to one of the following three categories, namely (1) supply relief centers, (2) demand relief centers, and (3) potential supply or demand relief centers (see Fig. 3). It is required to divide these relief centers into three categories because they have different decision variables. Then more details about these three categories are given based on the stock level S_t and the demand $\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\}$ overall scenarios.

(1) Supply relief-center category

$$S_t \geq \max_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} \tag{1}$$

where the inequality in (1) indicates that this relief center is considered as a supply point.

(2) Demand relief-center category

$$S_t \leq \min_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} \tag{2}$$

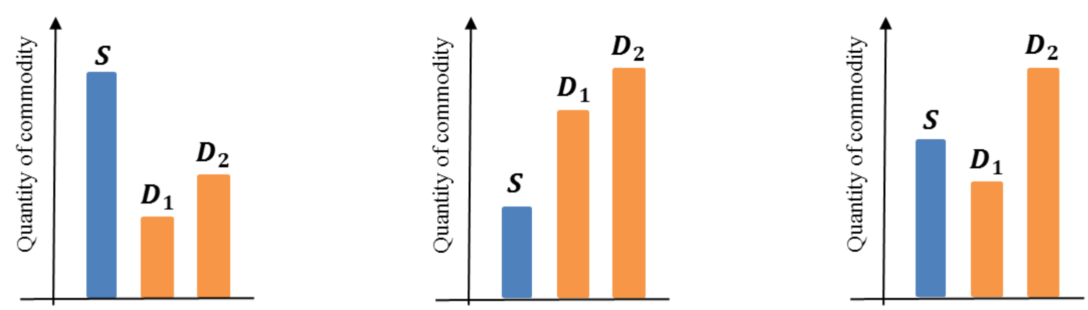
where the inequality in (2) indicates that this relief center is considered as a demand point.

(3) Potential supply or demand relief-center category

$$\min_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} < S_t < \max_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} \tag{3}$$

The above inequality in (3) shows that the stock level is between the minimum and maximum possible demand. It is difficult to tell that this relief center is a supply point or a demand point because it has the potential to send or receive commodities. This kind of relief centers belongs to the potential supply or demand relief-center category and needs to be identified as a demand or supply relief center.

To provide a visual illustration for the above three relief-center categories, three illustrative examples are provided in Fig. 3, where two scenarios are considered. As shown in Fig. 3, the stock level is denoted by S and the possible quantities of demand in two scenarios are denoted by D_1 and D_2. For the supply relief center shown in Fig. 3(a), there are two possible quantities of surplus (i.e., practical supply) that are $S - D_1$ and $S - D_2$. For the demand relief center shown in Fig. 3(b), there are two possible quantities of practical demand that are $D_1 - S$ and $D_2 - S$. For the supply or demand relief center shown in Fig. 3(c), the surplus is $S - D_1$ in the first scenario and the practical demand is $D_2 - S$ in the second scenario.



(a) Supply relief center (b) Demand relief center (c) Supply or demand relief center

Fig. 3. Illustrative examples for the three relief-center categories

As shown in Fig. 3, all the relief centers are divided into three categories after comparing the stock levels and the demands. Besides, the intersection of any two relief-center categories is zero. Thus, the actual supply (surplus) and actual demand (shortage) are identified for these three relief-center categories.

It is easily observed that the surplus happens in the first and third categories. Let $\mathcal{P}_{t\xi}$ be the surplus of commodity-type t in scenario ξ, which is represented by

$$\mathcal{P}_{t\xi} = \begin{cases} S_t - D_{t\xi} & \text{if } S_t \geq \max\limits_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} \\ \max\{S_t - D_{t\xi}, 0\} & \text{if } \min\limits_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} < S_t < \max\limits_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} \end{cases} \tag{4}$$

It is easily seen that the shortage happens in the second and third categories. Let $\mathcal{Q}_{t\xi}$ be the shortage of commodity-type t in scenario ξ, which is represented by

$$\mathcal{Q}_{t\xi} = \begin{cases} D_{t\xi} - S_t & \text{if } S_t \leq \min\limits_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} \\ \max\{D_{t\xi} - S_t, 0\} & \text{if } \min\limits_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} < S_t < \max\limits_{\xi}\{D_{t1}, D_{t2}, \dots, D_{t\xi}, \dots\} \end{cases} \tag{5}$$

With the above considerations, a similar situation can be identified after the outbreak of COVID-19 because the dissimilarly and unevenly distributed prevalence of infection are discrepant in different affected areas, which leads to a growing imbalance between the supply and demand. In this sense, the medical staff and supplies also need to be rebalanced among different areas in response to COVID-19. In addition, the demand for medical staff is also uncertain since the number of infected patients is quite difficult to be predicted. As a consequence, the main concerns of this study are also suitable for rebalancing the medical staff and supplies in response to COVID-19.

3.4 Goals

This research considers two goals; the first goal aims to achieve maximum fairness in rebalancing commodities and the second goal is to transport commodities as quickly as possible. Particularly, the minimization of the weighted proportion of unmet demand is used to measure fairness. The second goal is measured by the transportation time of vehicles and helicopters.

3.5 Presumptions

Three assumptions are postulated for the BOSMINP model.

(1) The locations and number of relief centers are given. Each relief center is a separate unit. Since the multi-commodity rebalancing process happens after the commodities are stocked or distributed at the relief centers, the locations and number of relief centers are known. At the same time, each of the relief centers is in charge of distributing the commodities to victims in an independent area, which indicates that the demand for commodities in this area is also independent. A similar action can be found in Gao (2020).

(2) The distances between relief centers are known, which is a common assumption and widely used in previous studies (Li et al. 2011; Chen and Yu 2016).

(3) Both vehicles and helicopters can transport mixed commodities together. In practice, the vehicles and helicopters are usually used to carry mixed commodities because the victims in the disaster area need a variety of commodities.

4. Mathematical model

4.1 Notations

Sets

$\mathcal{S}$:	Set of relief centers with surpluses, indexed by s.	$\mathcal{T}$:	Set of commodity types, indexed by t.
$\mathcal{D}$:	Set of relief centers with shortages, indexed by d.	$\varXi$:	Set of scenarios in supply and demand, indexed by ξ.
$\mathcal{R}$:	Set of supply or demand relief centers, indexed by r, l & $r \neq l$.	$\varPhi$:	Set of scenarios in road availability, indexed by ζ.

Stock level and priority Parameters

S_{ts}:	Stock level at relief-center $s \in \mathcal{S}$ for $t \in \mathcal{T}$.	P_{ts}:	Priority of relief-center $s \in \mathcal{S}$ for $t \in \mathcal{T}$.
S_{td}:	Stock level at relief-center $d \in \mathcal{D}$ for $t \in \mathcal{T}$	P_{td}:	Priority of relief-center $d \in \mathcal{D}$ for $t \in \mathcal{T}$.
S_{tr}:	Stock level at relief-center $r \in \mathcal{R}$ for $t \in \mathcal{T}$.	P_{tr}:	Priority of relief-center $r \in \mathcal{R}$ for $t \in \mathcal{T}$.

Distance parameters

T_{sd}:	Distance for vehicles between $s \in \mathcal{S}$ and $d \in \mathcal{D}$.	E_{sd}:	Distance for helicopters between $s \in \mathcal{S}$ and $d \in \mathcal{D}$.
T_{sr}:	Distance for vehicles between $s \in \mathcal{S}$ and $r \in \mathcal{R}$.	E_{sr}:	Distance for helicopters between $s \in \mathcal{S}$ and $r \in \mathcal{R}$.
T_{rd}:	Distance for vehicles between $r \in \mathcal{R}$ and $d \in \mathcal{D}$.	E_{rd}:	Distance for helicopters between $r \in \mathcal{R}$ and $d \in \mathcal{D}$.
T_{rl}:	Distance for vehicles between $r \in \mathcal{R}$ and $l \in \mathcal{R}$.	E_{rl}:	Distance for helicopters between $r \in \mathcal{R}$ and $l \in \mathcal{R}$.

Vehicle, helicopter, and commodity parameters

AV, AH:	Numbers of vehicles and helicopters, respectively.
W_t, V_t :	Weight and volume of $t \in \mathcal{T}$, respectively.
CW, CV:	Weight and volume capacities of vehicles, respectively.
HW, HV:	Weight and volume capacities of helicopters, respectively.
TV, TH:	Travel speeds of vehicles and helicopters, respectively.
LV, LH:	Loading/unloading times of vehicles and helicopters, respectively.

Demand parameters

D_{ts}^{ξ}:	Demand for $t \in \mathcal{T}$ at $s \in \mathcal{S}$ in $\xi \in \varXi$.	D_{tr}^{ξ}:	Demand for $t \in \mathcal{T}$ at $r \in \mathcal{R}$ in $\xi \in \varXi$.
D_{td}^{ξ}:	Demand for $t \in \mathcal{T}$ at $d \in \mathcal{D}$ in $\xi \in \varXi$.		

Road availability parameters

a_{sd}^{ζ}:	Availability between $s \in \mathcal{S}$ and $d \in \mathcal{D}$ in $\zeta \in \varPhi$.	a_{rd}^{ζ}:	Availability between $r \in \mathcal{R}$ and $d \in \mathcal{D}$ in $\zeta \in \varPhi$.
a_{sr}^{ζ}:	Availability between $s \in \mathcal{S}$ and $r \in \mathcal{R}$ in $\zeta \in \varPhi$.	a_{rl}^{ζ}:	Availability between $r \in \mathcal{R}$ and $l \in \mathcal{R}$ in $\zeta \in \varPhi$.

Probabilities

Pr_{ξ}:	Probability in $\xi \in \varXi$.	Pr_{ζ}:	Probability in $\zeta \in \varPhi$.

Decision variables

o_{ts}: Outgoing shipment at $s \in \mathcal{S}$ for $t \in \mathcal{T}$.

i_{td}: Incoming shipment at $d \in \mathcal{D}$ for $t \in \mathcal{T}$.

p_{tr}: Outgoing shipment at $r \in \mathcal{R}$ for $t \in \mathcal{T}$.

q_{tr}: Incoming shipment at $r \in \mathcal{R}$ for $t \in \mathcal{T}$.

$f_{sd}^{t\zeta}$: Flow of $t \in \mathcal{T}$ from $s \in \mathcal{S}$ to $d \in \mathcal{D}$ in $\zeta \in \Phi$.

$f_{sr}^{t\zeta}$: Flow of $t \in \mathcal{T}$ from $s \in \mathcal{S}$ to $r \in \mathcal{R}$ in $\zeta \in \Phi$.

$f_{rd}^{t\zeta}$: Flow of $t \in \mathcal{T}$ from $r \in \mathcal{R}$ to $d \in \mathcal{D}$ in $\zeta \in \Phi$.

$f_{rl}^{t\zeta}$: Flow of $t \in \mathcal{T}$ from $r \in \mathcal{R}$ to $l \in \mathcal{R}$ in $\zeta \in \Phi$.

n_{sd}^{ζ}: Number of vehicles from $s \in \mathcal{S}$ to $d \in \mathcal{D}$ in $\zeta \in \Phi$.

n_{sr}^{ζ}: Number of vehicles from $s \in \mathcal{S}$ to $r \in \mathcal{R}$ in $\zeta \in \Phi$.

n_{rd}^{ζ}: Number of vehicles from $r \in \mathcal{R}$ to $d \in \mathcal{D}$ in $\zeta \in \Phi$.

n_{rl}^{ζ}: Number of vehicles from $r \in \mathcal{R}$ to $l \in \mathcal{R}$ in $\zeta \in \Phi$.

h_{sd}^{ζ}: Number of helicopters from $s \in \mathcal{S}$ to $d \in \mathcal{D}$ in $\zeta \in \Phi$.

h_{sr}^{ζ}: Number of helicopters from $s \in \mathcal{S}$ to $r \in \mathcal{R}$ in $\zeta \in \Phi$.

h_{rd}^{ζ}: Number of helicopters from $r \in \mathcal{R}$ to $d \in \mathcal{D}$ in $\zeta \in \Phi$.

h_{rl}^{ζ}: Number of helicopters from $r \in \mathcal{R}$ to $l \in \mathcal{R}$ in $\zeta \in \Phi$.

4.2 Objective functions

This study considers two objectives; maximization of fairness and minimization of transportation time, which are introduced below.

4.2.1 Maximization of fairness

The maximization of fairness is formulated as the minimization of the weighted proportion of unmet demand. With the uncertain demand and supply, the weighted proportion of unmet demands at three relief-center categories are provided below.

- ***Weighted proportion of unmet demand at s***

Given the priority P_{ts}, stock level S_{ts}, and demand D_{ts}^{ξ} in scenario ξ at s, the weighted proportion of unmet demand $\boldsymbol{S}(o_{ts}, \xi)$ for commodity-type t is defined as

$$\boldsymbol{S}(o_{ts}, \xi) = P_{ts} \frac{\max\left\{D_{ts}^{\xi} - (S_{ts} - o_{ts}), 0\right\}}{D_{ts}^{\xi}} \tag{6}$$

- ***Weighted proportion of unmet demand at d***

Given the priority P_{td}, stock level S_{td}, and demand D_{td}^{ξ} in scenario ξ at d, the weighted proportion of unmet demand $\boldsymbol{D}(i_{td}, \xi)$ for commodity-type t is defined as

$$\boldsymbol{D}(i_{td}, \xi) = P_{td} \frac{\max\left\{D_{td}^{\xi} - (S_{td} + i_{td}), 0\right\}}{D_{td}^{\xi}} \tag{7}$$

- ***Weighted proportion of unmet demand at r***

Given the priority P_{tr}, stock level S_{tr}, and demand D_{tr}^{ξ} in scenario ξ at r, the weighted proportion of unmet demand $\boldsymbol{R}(p_{tr}, q_{tr}, \xi)$ for commodity-type t is defined as

$$\boldsymbol{R}(p_{tr}, q_{tr}, \xi) = P_{tr} \frac{\max\left\{D_{tr}^{\xi} - (S_{tr} - p_{tr} + q_{tr}), 0\right\}}{D_{tr}^{\xi}} \tag{8}$$

Then the expected weighted proportion of unmet demand at three relief-center categories are denoted by $\mathbb{E}[\boldsymbol{S}(o_{ts}, \xi)]$, $\mathbb{E}[\boldsymbol{D}(i_{td}, \xi)]$, and $\mathbb{E}[\boldsymbol{R}(p_{tr}, q_{tr}, \xi)]$, respectively. They are given by

$$\mathbb{E}[\boldsymbol{S}(o_{ts}, \xi)] = P_{ts} \sum_{\xi \in \Xi} Pr_{\xi} \frac{\max\left\{D_{ts}^{\xi} - (S_{ts} - o_{ts}), 0\right\}}{D_{ts}^{\xi}} \tag{9}$$

$$\mathbb{E}[\boldsymbol{D}(i_{td}, \xi)] = P_{td} \sum_{\xi \in \Xi} Pr_{\xi} \frac{\max\left\{D_{td}^{\xi} - (S_{td} + i_{td}), 0\right\}}{D_{td}^{\xi}} \tag{10}$$

$$\mathbb{E}[\boldsymbol{R}(p_{tr}, q_{tr}, \xi)] = P_{tr} \sum_{\xi \in \Xi} Pr_{\xi} \frac{\max\left\{D_{tr}^{\xi} - (S_{tr} - p_{tr} + q_{tr}), 0\right\}}{D_{tr}^{\xi}} \tag{11}$$

Therefore, the first objective function Ψ_1 is given by

$$\Psi_1 = \sum_{t \in \mathcal{T}} \sum_{s \in \mathcal{S}} \mathbb{E}[\boldsymbol{S}(o_{ts}, \xi)] + \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} \mathbb{E}[\boldsymbol{D}(i_{td}, \xi)] + \sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{R}} \mathbb{E}[\boldsymbol{R}(p_{tr}, q_{tr}, \xi)] \tag{12}$$

4.2.2 Transportation time

The second objective aims to minimize the total transportation time. Firstly, the transportation time for vehicles is considered. Specifically, the transportation time $VT\left(n_{sd}^{\zeta}\right)$ on the route between s and d in scenario ζ is formulated as

$$VT\left(n_{sd}^{\zeta}\right) = \left(LV + \frac{T_{sd}}{TV \cdot a_{sd}^{\zeta}}\right) n_{sd}^{\zeta} \tag{13}$$

The expected transportation time $\mathbb{E}\left[VT\left(n_{sd}^{\zeta}\right)\right]$ on the route connecting s and d over all scenarios is given by

$$\mathbb{E}\left[VT\left(n_{sd}^{\zeta}\right)\right] = \sum_{\zeta \in \Phi} Pr_{\zeta} \left(LV + \frac{T_{sd}}{TV \cdot a_{sd}^{\zeta}}\right) n_{sd}^{\zeta} \tag{14}$$

Similarly, the expected transportation times $\mathbb{E}\left[VT\left(n_{sr}^{\zeta}\right)\right]$, $\mathbb{E}\left[VT\left(n_{rd}^{\zeta}\right)\right]$, and $\mathbb{E}\left[VT\left(n_{rl}^{\zeta}\right)\right]$ on the routes s to r, r to d, and r to l are formulated as

$$\mathbb{E}\left[VT\left(n_{sr}^{\zeta}\right)\right] = \sum_{\zeta \in \Phi} Pr_{\zeta} \left(LV + \frac{T_{sr}}{TV \cdot a_{sr}^{\zeta}}\right) n_{sr}^{\zeta} \tag{15}$$

$$\mathbb{E}\left[VT\left(n_{rd}^{\zeta}\right)\right] = \sum_{\zeta\in\Phi} Pr_{\zeta}\left(LV + \frac{T_{rd}}{TV\cdot a_{rd}^{\zeta}}\right)n_{rd}^{\zeta} \tag{16}$$

$$\mathbb{E}\left[VT\left(n_{rl}^{\zeta}\right)\right] = \sum_{\zeta\in\Phi} Pr_{\zeta}\left(LV + \frac{T_{rl}}{TV\cdot a_{rl}^{\zeta}}\right)n_{rl}^{\zeta} \tag{17}$$

Then the transportation time for helicopters can be formulated. Similar to the above method, the expected transportation times $\mathbb{E}\left[HT\left(h_{sd}^{\zeta}\right)\right]$, $\mathbb{E}\left[HT\left(h_{sr}^{\zeta}\right)\right]$, $\mathbb{E}\left[HT\left(h_{rd}^{\zeta}\right)\right]$, and $\mathbb{E}\left[HT\left(h_{rl}^{\zeta}\right)\right]$ on the routes, s to d , s to r, r to d, and r to l are formulated as

$$\mathbb{E}\left[HT\left(h_{sd}^{\zeta}\right)\right] = \sum_{\zeta\in\Phi} Pr_{\zeta}\left(LH + \frac{E_{sd}}{TH}\right)h_{sd}^{\zeta} \tag{18}$$

$$\mathbb{E}\left[HT\left(h_{sr}^{\zeta}\right)\right] = \sum_{\zeta\in\Phi} Pr_{\zeta}\left(LH + \frac{E_{sr}}{TH}\right)h_{sr}^{\zeta} \tag{19}$$

$$\mathbb{E}\left[HT\left(h_{rd}^{\zeta}\right)\right] = \sum_{\zeta\in\Phi} Pr_{\zeta}\left(LH + \frac{E_{rd}}{TH}\right)h_{rd}^{\zeta} \tag{20}$$

$$\mathbb{E}\left[HT\left(h_{rl}^{\zeta}\right)\right] = \sum_{\zeta\in\Phi} Pr_{\zeta}\left(LH + \frac{E_{rl}}{TH}\right)h_{rl}^{\zeta} \tag{21}$$

Then the second objective function Ψ_2 is given by

$$\begin{aligned}\Psi_2 = &\sum_{s\in\mathcal{S}}\sum_{d\in\mathcal{D}}\left\{\mathbb{E}\left[VT\left(n_{sd}^{\zeta}\right)\right] + \mathbb{E}\left[HT\left(h_{sd}^{\zeta}\right)\right]\right\} + \sum_{s\in\mathcal{S}}\sum_{r\in\mathcal{R}}\left\{\mathbb{E}\left[VT\left(n_{sr}^{\zeta}\right)\right] + \mathbb{E}\left[HT\left(h_{sr}^{\zeta}\right)\right]\right\} \\ &+ \sum_{r\in\mathcal{R}}\sum_{d\in\mathcal{D}}\left\{\mathbb{E}\left[VT\left(n_{rd}^{\zeta}\right)\right] + \mathbb{E}\left[HT\left(h_{rd}^{\zeta}\right)\right]\right\} + \sum_{r\in\mathcal{R}}\sum_{l\in\mathcal{R}}\left\{\mathbb{E}\left[VT\left(n_{rl}^{\zeta}\right)\right] + \mathbb{E}\left[HT\left(h_{rl}^{\zeta}\right)\right]\right\}\end{aligned} \tag{22}$$

4.3 Mathematical formulation

The MCRT problem is formulated as the following BOSMINP model.

$$\begin{aligned}\text{Min}\quad \Psi_1 = &\sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}} P_{ts}\sum_{\xi\in\Xi} Pr_{\xi}\frac{\max\left\{D_{ts}^{\xi} - (S_{ts} - o_{ts}), 0\right\}}{D_{ts}^{\xi}} + \sum_{t\in\mathcal{T}}\sum_{d\in\mathcal{D}} P_{td}\sum_{\xi\in\Xi} Pr_{\xi}\frac{\max\left\{D_{td}^{\xi} - (S_{td} + i_{td}), 0\right\}}{D_{td}^{\xi}} \\ &+ \sum_{t\in\mathcal{T}}\sum_{r\in\mathcal{R}} P_{tr}\sum_{\xi\in\Xi} Pr_{\xi}\frac{\max\left\{D_{tr}^{\xi} - (S_{tr} - p_{tr} + q_{tr}), 0\right\}}{D_{tr}^{\xi}}\end{aligned} \tag{23}$$

$$
\begin{aligned}
\text{Min}\ \ \Psi_2 = &\sum_{s\in\mathcal{S}}\sum_{d\in\mathcal{D}}\sum_{\zeta\in\Phi} Pr_\zeta\left[\left(LV + \frac{T_{sd}}{TVa_{sd}^{\zeta}}\right)n_{sd}^{\zeta} + \left(LH + \frac{E_{sd}}{TH}\right)h_{sd}^{\zeta}\right] \\
&+ \sum_{s\in\mathcal{S}}\sum_{r\in\mathcal{R}}\sum_{\zeta\in\Phi} Pr_\zeta\left[\left(LV + \frac{T_{sr}}{TVa_{sr}^{\zeta}}\right)n_{sr}^{\zeta} + \left(LH + \frac{E_{sr}}{TH}\right)h_{sr}^{\zeta}\right] \\
&+ \sum_{r\in\mathcal{R}}\sum_{d\in\mathcal{D}}\sum_{\zeta\in\Phi} Pr_\zeta\left[\left(LV + \frac{T_{rd}}{TVa_{rd}^{\zeta}}\right)n_{rd}^{\zeta} + \left(LH + \frac{E_{rd}}{TH}\right)h_{rd}^{\zeta}\right] \\
&+ \sum_{r\in\mathcal{R}}\sum_{l\in\mathcal{R}}\sum_{\zeta\in\Phi} Pr_\zeta\left[\left(LV + \frac{T_{rl}}{TVa_{rl}^{\zeta}}\right)n_{rl}^{\zeta} + \left(LH + \frac{E_{rl}}{TH}\right)h_{rl}^{\zeta}\right]
\end{aligned} \tag{24}
$$

s.t.

$$\sum_{d\in\mathcal{D}} i_{td} + \sum_{r\in\mathcal{R}} q_{tr} = \sum_{s\in\mathcal{S}} o_{ts} + \sum_{r\in\mathcal{R}} p_{tr} \qquad \forall\, t\in\mathcal{T}. \tag{25}$$

$$\min\left\{D_{ts}^1, D_{ts}^2, \dots, D_{ts}^{\xi}, \dots\right\} \le S_{ts} - o_{ts} \le \max\left\{D_{ts}^1, D_{ts}^2, \dots, D_{ts}^{\xi}, \dots\right\} \qquad \forall\, t\in\mathcal{T}, s\in\mathcal{S}. \tag{26}$$

$$\min\left\{D_{tr}^1, D_{tr}^2, \dots, D_{tr}^{\xi}, \dots\right\} \le S_{td} + i_{td} \le \max\left\{D_{tr}^1, D_{tr}^2, \dots, D_{tr}^{\xi}, \dots\right\} \qquad \forall\, t\in\mathcal{T}, d\in\mathcal{D}. \tag{27}$$

$$\min\left\{D_{tr}^1, D_{tr}^2, \dots, D_{tr}^{\xi}, \dots\right\} \le S_{tr} - p_{tr} + q_{tr} \le \max\left\{D_{tr}^1, D_{tr}^2, \dots, D_{tr}^{\xi}, \dots\right\} \qquad \forall\, t\in\mathcal{T}, r\in\mathcal{R}. \tag{28}$$

$$p_{tr}\cdot q_{tr} = 0 \qquad \forall\, t\in\mathcal{T}, r\in\mathcal{R}. \tag{29}$$

o_{ts}, i_{td}, p_{tr}, and q_{tr} are nonnegative variables $\qquad \forall\, t\in\mathcal{T}, s\in\mathcal{S}, d\in\mathcal{D}.$ (30)

$$\sum_{d\in\mathcal{D}} f_{sd}^{t\zeta} + \sum_{r\in\mathcal{R}} f_{sr}^{t\zeta} \le o_{ts} \qquad \forall\, t\in\mathcal{T}, s\in\mathcal{S}, \zeta\in\Phi. \tag{31}$$

$$\sum_{s\in\mathcal{S}} f_{sd}^{t\zeta} + \sum_{r\in\mathcal{R}} f_{rd}^{t\zeta} \ge i_{td} \qquad \forall\, t\in\mathcal{T}, d\in\mathcal{D}, \zeta\in\Phi. \tag{32}$$

$$\sum_{d\in\mathcal{D}} f_{rd}^{t\zeta} + \sum_{l\in\mathcal{R}} f_{rl}^{t\zeta} \le p_{tr} \qquad \forall\, t\in\mathcal{T}, r\in\mathcal{R}, \zeta\in\Phi. \tag{33}$$

$$\sum_{s\in\mathcal{S}} f_{sr}^{t\zeta} + \sum_{l\in\mathcal{R}} f_{lr}^{t\zeta} \ge q_{tr} \qquad \forall\, t\in\mathcal{T}, r\in\mathcal{R}, \zeta\in\Phi. \tag{34}$$

$$
\begin{aligned}
&\sum_{s\in\mathcal{S}}\left(\sum_{d\in\mathcal{D}} f_{sd}^{t\zeta} + \sum_{r\in\mathcal{R}} f_{sr}^{t\zeta}\right) + \sum_{r\in\mathcal{R}}\left(\sum_{d\in\mathcal{D}} f_{rd}^{t\zeta} + \sum_{l\in\mathcal{R}} f_{rl}^{t\zeta}\right) \\
&\qquad = \sum_{d\in\mathcal{D}}\left(\sum_{s\in\mathcal{S}} f_{sd}^{t\zeta} + \sum_{r\in\mathcal{R}} f_{rd}^{t\zeta}\right) + \sum_{r\in\mathcal{R}}\left(\sum_{s\in\mathcal{S}} f_{sr}^{t\zeta} + \sum_{l\in\mathcal{R}} f_{lr}^{t\zeta}\right) \qquad \forall\, t\in\mathcal{T}, \zeta\in\Phi.
\end{aligned} \tag{35}
$$

$$\sum_{t\in\mathcal{T}} f_{sd}^{t\zeta}\cdot W_t \le n_{sd}^{\zeta}\cdot CW + h_{sd}^{\zeta}\cdot HW \qquad \forall\, s\in\mathcal{S}, d\in\mathcal{D}, \zeta\in\Phi. \tag{36}$$

$$\sum_{t\in\mathcal{T}} f_{sd}^{t\zeta}\cdot V_t \le n_{sd}^{\zeta}\cdot CV + h_{sd}^{\zeta}\cdot HV \qquad \forall\, s\in\mathcal{S}, d\in\mathcal{D}, \zeta\in\Phi. \tag{37}$$

$$\sum_{t\in\mathcal{T}} f_{sr}^{t\zeta}\cdot W_t \le n_{sr}^{\zeta}\cdot CW + h_{sr}^{\zeta}\cdot HW \qquad \forall\, s\in\mathcal{S}, r\in\mathcal{R}, \zeta\in\Phi. \tag{38}$$

$$\sum_{t\in\mathcal{T}} f_{sr}^{t\zeta}\cdot V_t \le n_{sr}^{\zeta}\cdot CV + h_{sr}^{\zeta}\cdot HV \qquad \forall\, s\in\mathcal{S}, r\in\mathcal{R}, \zeta\in\Phi. \tag{39}$$

$$\sum_{t\in\mathcal{T}} f_{rd}^{t\zeta} \cdot W_t \leq n_{rd}^{\zeta} \cdot CW + h_{rd}^{\zeta} \cdot HW \qquad \forall\, r \in \mathcal{R}, d \in \mathcal{D}, \zeta \in \Phi. \tag{40}$$

$$\sum_{t\in\mathcal{T}} f_{rd}^{t\zeta} \cdot V_t \leq n_{rd}^{\zeta} \cdot CV + h_{rd}^{\zeta} \cdot HV \qquad \forall\, r \in \mathcal{R}, d \in \mathcal{D}, \zeta \in \Phi. \tag{41}$$

$$\sum_{t\in\mathcal{T}} f_{rl}^{t\zeta} \cdot W_t \leq n_{rl}^{\zeta} \cdot CW + h_{rl}^{\zeta} \cdot HW \qquad \forall\, r \in \mathcal{R}, l \in \mathcal{R}, \zeta \in \Phi. \tag{42}$$

$$\sum_{t\in\mathcal{T}} f_{rl}^{t\zeta} \cdot V_t \leq n_{rl}^{\zeta} \cdot CV + h_{rl}^{\zeta} \cdot HV \qquad \forall\, r \in \mathcal{R}, l \in \mathcal{R}, \zeta \in \Phi. \tag{43}$$

$$\sum_{s\in\mathcal{S}}\sum_{d\in\mathcal{D}} n_{sd}^{\zeta} + \sum_{s\in\mathcal{S}}\sum_{r\in\mathcal{R}} n_{sr}^{\zeta} + \sum_{r\in\mathcal{R}}\sum_{d\in\mathcal{D}} n_{rd}^{\zeta} + \sum_{r\in\mathcal{R}}\sum_{l\in\mathcal{R}} n_{rl}^{\zeta} \leq AV \qquad \forall\, \zeta \in \Phi. \tag{44}$$

$$\sum_{s\in\mathcal{S}}\sum_{d\in\mathcal{D}} h_{sd}^{\zeta} + \sum_{s\in\mathcal{S}}\sum_{r\in\mathcal{R}} h_{sr}^{\zeta} + \sum_{r\in\mathcal{R}}\sum_{d\in\mathcal{D}} h_{rd}^{\zeta} + \sum_{r\in\mathcal{R}}\sum_{l\in\mathcal{R}} h_{rl}^{\zeta} \leq AH \qquad \forall\, \zeta \in \Phi. \tag{45}$$

$f_{sd}^{t\zeta}, f_{sr}^{t\zeta}, f_{rd}^{t\zeta}$, and $f_{rl}^{t\zeta}$ are nonnegative variables. (46)

$n_{sd}^{\zeta}, n_{sr}^{\zeta}, n_{rd}^{\zeta}, n_{rl}^{\zeta}, h_{sd}^{\zeta}, h_{sr}^{\zeta}, h_{rd}^{\zeta}$, and h_{rl}^{ζ} are non-negative integer variables. (47)

The first objective function (23) is to maximize fairness and the second objective function (24) is the minimization of the total transportation time. Constraint (25) restricts the balance between incoming and outgoing shipments. Constraints (26)-(28) guarantee that the results are within the feasible regions. Constraint (29) guarantees that r chooses to send or receive commodities. Constraint (30) defines the decision variables. Constraints (31) and (33) restrict the quantities of sent commodities. Constraints (32) and (34) ensure the quantities of received commodities. Constraint (35) ensures the transportation balance between incoming and outgoing flows. Constraints (36)-(43) guarantee that the vehicles and helicopters can transport mixed commodities from s to d, from s to r, from r to d, and from r to l, respectively. Constraints (44) and (45) restrict the numbers of vehicles and helicopters, respectively. Constraints (46) and (47) denote the decision variables.

4.4 Linearization method

The proposed BOSMINP model is nonlinear due to the objective function (23) and Constraint (29). It is necessary to develop a linearization method for the BOSMINP model. Particularly, the proposed model can be linearized by introducing several auxiliary parameters and variables (i.e., a big positive value M and five binary variables) into the model, which are given by

$$\jmath_{ts}^{\xi} = \begin{cases} 1 & \text{if } D_{ts}^{\xi} > S_{ts} - o_{ts} \\ 0 & \text{otherwise} \end{cases} \qquad \forall\, s \in \mathcal{S}, t \in \mathcal{T}, \xi \in \Xi. \tag{48}$$

$$\hbar_{td}^{\xi} = \begin{cases} 1 & \text{if } D_{td}^{\xi} > S_{td} + i_{td} \\ 0 & \text{otherwise} \end{cases} \qquad \forall\, d \in \mathcal{D}, t \in \mathcal{T}, \xi \in \Xi. \tag{49}$$

$$\ell_{tr}^{\xi} = \begin{cases} 1 & \text{if } D_{tr}^{\xi} > S_{tr} - p_{tr} + q_{tr} \\ 0 & \text{otherwise} \end{cases} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}, \xi \in \Xi. \tag{50}$$

$$\wp_{tr} = \begin{cases} 1 & \text{if } p_{tr} > 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{51}$$

$$q_{tr} = \begin{cases} 1 & \text{if } q_{tr} > 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{52}$$

Then the proposed BOSMINP model is reformulated as the following bi-objective optimization model $\boldsymbol{\mathcal{A}}$.

$\boldsymbol{\mathcal{A}}$:

$$\begin{aligned} \text{Min} \quad \Psi_{1L} = & \sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}} P_{ts} \sum_{\xi\in\Xi} Pr_{\xi} \frac{\left[D_{ts}^{\xi} - (S_{ts} - o_{ts})\right] j_{ts}^{\xi}}{D_{ts}^{\xi}} + \sum_{t\in\mathcal{T}}\sum_{d\in\mathcal{D}} P_{td} \sum_{\xi\in\Xi} Pr_{\xi} \frac{\left[D_{td}^{\xi} - (S_{td} + i_{td})\right] k_{td}^{\xi}}{D_{td}^{\xi}} \\ & + \sum_{t\in\mathcal{T}}\sum_{r\in\mathcal{R}} P_{tr} \sum_{\xi\in\Xi} Pr_{\xi} \frac{\left[D_{tr}^{\xi} - (S_{tr} - p_{tr} + q_{tr})\right] \ell_{tr}^{\xi}}{D_{tr}^{\xi}} \end{aligned} \tag{53}$$

Min Ψ_2

s.t.

Constraints (25)-(28), (31)-(47).

$$D_{ts}^{\xi} - (S_{ts} - o_{ts}) \geq \left(j_{ts}^{\xi} - 1\right) \cdot M \quad \forall\, s \in \mathcal{S}, t \in \mathcal{T}, \xi \in \Xi. \tag{54}$$

$$D_{ts}^{\xi} - (S_{ts} - o_{ts}) \leq j_{ts}^{\xi} \cdot M \quad \forall\, s \in \mathcal{S}, t \in \mathcal{T}, \xi \in \Xi. \tag{55}$$

$$D_{td}^{\xi} - (S_{td} + i_{td}) \geq \left(k_{td}^{\xi} - 1\right) \cdot M \quad \forall\, d \in \mathcal{D}, t \in \mathcal{T}, \xi \in \Xi. \tag{56}$$

$$D_{td}^{\xi} - (S_{td} + i_{td}) \leq k_{td}^{\xi} \cdot M \quad \forall\, d \in \mathcal{D}, t \in \mathcal{T}, \xi \in \Xi. \tag{57}$$

$$D_{tr}^{\xi} - (S_{tr} - p_{tr} + q_{tr}) \geq \left(\ell_{tr}^{\xi} - 1\right) \cdot M \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}, \xi \in \Xi. \tag{58}$$

$$D_{tr}^{\xi} - (S_{tr} - p_{tr} + q_{tr}) \leq \ell_{tr}^{\xi} M \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}, \xi \in \Xi. \tag{59}$$

$$\wp_{tr} + q_{tr} \leq 1 \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{60}$$

$$p_{tr} \leq \wp_{tr} \cdot M \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{61}$$

$$q_{tr} \leq q_{tr} \cdot M \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{62}$$

The reformulated objective function as the Eq. (53) is the same as the objective function in (23). Constraints (54) and (55) guarantee the non-negative of the unmet demand at s. Constraints (56) and (57) guarantee the non-negative of the unmet demand at d. Constraints (58) and (59) guarantee the non-negative of the unmet demand at r. Constraints (60)-(62) restrict the non-negative outgoing or incoming shipment at r. The proofs for the above constraints are provided in the **Supplementary Materials**.

5. Solution strategy

Since the BOSMINP model contains two conflicting objectives, generating a set of efficient Pareto solutions is the primary goal (Dai and Charkhgard 2017) to understand the trade-off between them. Therefore, an adaptive augmented $\mathcal{E}$-constraint method is developed. When the size of the problem is getting larger, it becomes more difficult to obtain efficient solutions. To overcome the above difficulty, the model can be reformulated to obtain an upper bound for the second objective function before the optimal solution is determined. In what follows, these methods are introduced in detail.

5.1 Augmented $\mathcal{E}$-constraint method

Many methods have been developed to handle the bi-objective problems. These widely used techniques in practice contain $\mathcal{E}$-constraint, weighted sum, weighted metric, and lexicographic goal programming approaches. In this study, the $\mathcal{E}$-constraint method proposed by Haimes et al. (Haimes 1971) is adopted due to various advantages. For more details about the advantages of the Epsilon-constraint method, readers are referred to Mavrotas (2009) and Mohamadi and Yaghoubi (2017). The main idea is that an objective function is optimized while other objective functions are converted into constraints. Specifically, this study calculates the optimal Ψ_{1L} and the optimal multi-commodity rebalancing strategy ${o_{ts}}^*$, ${i_{td}}^*$, ${p_{tr}}^*$, and ${q_{tr}}^*$ with eliminating Ψ_2. Then the first objective function value $\mathcal{E}_1$ can be augmented by decreasing or increasing the total shipment between relief centers. Here, this study chooses to decrease the total shipment so that a set of Pareto-optimal solutions can be obtained. Thus, the model $\boldsymbol{\mathcal{A}}$ can be formulated as the following model $\boldsymbol{\mathcal{B}}$.

$\boldsymbol{\mathcal{B}}$:

$$\text{Min } \Psi_2 \tag{63}$$

s.t.

$$\Psi_{1L} \leq \mathcal{E}_1 \tag{64}$$

Constraints (25)-(28), (31)-(47), and (54)-(62).

5.2 Solution strategy for large-sized problems

When the problem size is getting larger, it is difficult to obtain the optimal solution within a limited time due to the complicated transportation of mixed commodities. In this sense, the BOSMINP model can be reformulated to obtain an upper-bound for Ψ_2, where the helicopters and vehicles are restricted to carry only one single-commodity type. In this sense, this study minimizes the upper-bound total transportation time, denoted by ${\Psi_2}^{\mathrm{u}}$, where the following eight temporary variables are needed.

$u_{sd}^{t\zeta}$: Assigned vehicles delivering $t \in \mathcal{T}$ from $s \in \mathcal{S}$ to $d \in \mathcal{D}$ in ζ

$u_{sr}^{t\zeta}$: Assigned vehicles delivering $t \in \mathcal{T}$ from $s \in \mathcal{S}$ to $r \in \mathcal{R}$ in ζ

$u_{rd}^{t\zeta}$: Assigned vehicles delivering $t \in \mathcal{T}$ from $r \in \mathcal{R}$ to $d \in \mathcal{D}$ in ζ

$u_{rl}^{t\zeta}$: Assigned vehicles delivering $t \in \mathcal{T}$ from $r \in \mathcal{R}$ to $l \in \mathcal{R}$ in ζ

$v_{sd}^{t\zeta}$: Assigned helicopters delivering $t \in \mathcal{T}$ from $s \in \mathcal{S}$ to $d \in \mathcal{D}$ in ζ

$v_{sr}^{t\zeta}$: Assigned helicopters delivering $t \in \mathcal{T}$ from $s \in \mathcal{S}$ to $r \in \mathcal{R}$ in ζ

$v_{rd}^{t\zeta}$: Assigned helicopters delivering $t \in \mathcal{T}$ from $r \in \mathcal{R}$ to $d \in \mathcal{D}$ in ζ

$v_{rl}^{t\zeta}$: Assigned helicopters delivering $t \in \mathcal{T}$ from $r \in \mathcal{R}$ to $l \in \mathcal{R}$ in ζ

Then the model $\boldsymbol{\mathcal{B}}$ can be reformulated as the following model $\boldsymbol{\mathcal{H}}$.

$\boldsymbol{\mathcal{H}}$:

$$\begin{aligned}\text{Min } \Psi_2{}^{\mathrm{u}} = \sum_{t\in\mathcal{T}} \Bigg\{ &\sum_{s\in\mathcal{S}} \sum_{d\in\mathcal{D}} \sum_{\zeta\in\Phi} Pr_\zeta \left[\left(LV + \frac{T_{sd}}{TV \cdot a_{sd}^{\zeta}} \right) u_{sd}^{t\zeta} + \left(LH + \frac{E_{sd}}{TH} \right) v_{sd}^{t\zeta} \right] \\ &+ \sum_{s\in\mathcal{S}} \sum_{r\in\mathcal{R}} \sum_{\zeta\in\Phi} Pr_\zeta \left[\left(LV + \frac{T_{sr}}{TV \cdot a_{sr}^{\zeta}} \right) u_{sr}^{t\zeta} + \left(LH + \frac{E_{sr}}{TH} \right) v_{sr}^{t\zeta} \right] \\ &+ \sum_{r\in\mathcal{R}} \sum_{d\in\mathcal{D}} \sum_{\zeta\in\Phi} Pr_\zeta \left[\left(LV + \frac{T_{rd}}{TV \cdot a_{rd}^{\zeta}} \right) u_{rd}^{t\zeta} + \left(LH + \frac{E_{rd}}{TH} \right) v_{rd}^{t\zeta} \right] \\ &+ \sum_{r\in\mathcal{R}} \sum_{l\in\mathcal{R}} \sum_{\zeta\in\Phi} Pr_\zeta \left[\left(LV + \frac{T_{rl}}{TV \cdot a_{rl}^{\zeta}} \right) u_{rl}^{t\zeta} + \left(LH + \frac{E_{rl}}{TH} \right) v_{rl}^{t\zeta} \right] \Bigg\}\end{aligned} \tag{65}$$

s.t.

$$\Psi_{1L} \leq \mathcal{E}_1 \tag{66}$$

Constraints (25)-(28), (30), (46), and (54)-(62).

$$W_t \cdot f_{sd}^{t\zeta} \leq CW \cdot u_{sd}^{t\zeta} + HW \cdot v_{sd}^{t\zeta} \qquad \forall\, t \in \mathcal{T}, s \in \mathcal{S}, d \in \mathcal{D}, \zeta \in \Phi. \tag{67}$$

$$V_t \cdot f_{sd}^{t\zeta} \leq CV \cdot u_{sd}^{t\zeta} + HV \cdot v_{sd}^{t\zeta} \qquad \forall\, t \in \mathcal{T}, s \in \mathcal{S}, d \in \mathcal{D}, \zeta \in \Phi. \tag{68}$$

$$W_t \cdot f_{sr}^{t\zeta} \leq CW \cdot u_{sr}^{t\zeta} + HW \cdot v_{sr}^{t\zeta} \qquad \forall\, t \in \mathcal{T}, s \in \mathcal{S}, r \in \mathcal{R}, \zeta \in \Phi. \tag{69}$$

$$V_t \cdot f_{sr}^{t\zeta} \leq CV \cdot u_{sr}^{t\zeta} + HV \cdot v_{sr}^{t\zeta} \qquad \forall\, t \in \mathcal{T}, s \in \mathcal{S}, r \in \mathcal{R}, \zeta \in \Phi. \tag{70}$$

$$W_t \cdot f_{rd}^{t\zeta} \leq CW \cdot u_{rd}^{t\zeta} + HW \cdot v_{rd}^{t\zeta} \qquad \forall\, t \in \mathcal{T}, r \in \mathcal{R}, d \in \mathcal{D}, \zeta \in \Phi. \tag{71}$$

$$V_t \cdot f_{rd}^{t\zeta} \leq CV \cdot u_{rd}^{t\zeta} + HV \cdot v_{rd}^{t\zeta} \qquad \forall\, t \in \mathcal{T}, r \in \mathcal{R}, d \in \mathcal{D}, \zeta \in \Phi. \tag{72}$$

$$W_t \cdot f_{rl}^{t\zeta} \leq CW \cdot u_{rl}^{t\zeta} + HW \cdot v_{rl}^{t\zeta} \qquad \forall\, t \in \mathcal{T}, r \in \mathcal{R}, l \in \mathcal{R}, \zeta \in \Phi. \tag{73}$$

$$V_t \cdot f_{rl}^{t\zeta} \leq CV \cdot u_{rl}^{t\zeta} + HV \cdot v_{rl}^{t\zeta} \qquad \forall\, t \in \mathcal{T}, r \in \mathcal{R}, l \in \mathcal{R}, \zeta \in \Phi. \tag{74}$$

$$\sum_{t\in\mathcal{T}} \left(\sum_{s\in\mathcal{S}} \sum_{d\in\mathcal{D}} u_{sd}^{t\zeta} + \sum_{s\in\mathcal{S}} \sum_{r\in\mathcal{R}} u_{sr}^{t\zeta} + \sum_{r\in\mathcal{R}} \sum_{d\in\mathcal{D}} u_{rd}^{t\zeta} + \sum_{r\in\mathcal{R}} \sum_{l\in\mathcal{R}} u_{rl}^{t\zeta} \right) \leq AV \qquad \forall\, \zeta \in \Phi. \tag{75}$$

$$\sum_{t\in\mathcal{T}} \left(\sum_{s\in\mathcal{S}} \sum_{d\in\mathcal{D}} v_{sd}^{t\zeta} + \sum_{s\in\mathcal{S}} \sum_{r\in\mathcal{R}} v_{sr}^{t\zeta} + \sum_{r\in\mathcal{R}} \sum_{d\in\mathcal{D}} v_{rd}^{t\zeta} + \sum_{r\in\mathcal{R}} \sum_{l\in\mathcal{R}} v_{rl}^{t\zeta} \right) \leq AH \qquad \forall\, \zeta \in \Phi. \tag{76}$$

$u_{sd}^{t\zeta}, u_{sr}^{t\zeta}, u_{rd}^{t\zeta}, u_{rl}^{t\zeta}, v_{sd}^{t\zeta}, v_{sr}^{t\zeta}, v_{rd}^{t\zeta}$, and $v_{rl}^{t\zeta}$ are non-negative integer variables. (77)

where the objective function in (65) is the upper-bound total transportation time. Constraints (67)-(74) restrict that the vehicles and helicopters can transport each single commodity type from s to d, from s to r, from r to d, and from r to l, respectively. Constraints (75) and (76) restrict the total numbers of vehicles and helicopters, respectively. Constraint (77) defines the decision variables.

After the optimal commodity flows (i.e., $f_{sd}^{t\zeta*}$, $f_{sr}^{t\zeta*}$, $f_{rd}^{t\zeta*}$, and $f_{rl}^{t\zeta*}$) are obtained in model $\boldsymbol{\mathcal{H}}$**,** where the vehicles and helicopters only carry a single commodity type under constraints (67)-(74), which may result in residual space in the vehicles and helicopters. To make full use of the capacities of the vehicles and helicopters, transporting mixed commodities is allowed based on optimal commodity flows obtained in model $\boldsymbol{\mathcal{H}}$. In this sense, the numbers of vehicles and helicopters can be further reduced and easily obtained in model $\boldsymbol{\mathcal{F}}$, which is formulated to obtain the final transit-related decisions.

$\boldsymbol{\mathcal{F}}$:

Min Ψ_2

s.t.

Constraints (44), (45), and (47).

$$\sum_{t\in\mathcal{T}} f_{sd}^{t\zeta*}\cdot W_t \le n_{sd}^{\zeta}\cdot CW + h_{sd}^{\zeta}\cdot HW, \sum_{t\in\mathcal{T}} f_{sd}^{t\zeta*}\cdot V_t \le n_{sd}^{\zeta}\cdot CV + h_{sd}^{\zeta}\cdot HV \qquad \forall\, s\in\mathcal{S}, d\in\mathcal{D}, \zeta\in\Phi. \tag{78}$$

$$\sum_{t\in\mathcal{T}} f_{sr}^{t\zeta*}\cdot W_t \le n_{sd}^{\zeta}\cdot CW + h_{sd}^{\zeta}\cdot HW, \sum_{t\in\mathcal{T}} f_{sr}^{t\zeta*}\cdot V_t \le n_{sr}\cdot CV + h_{sr}\cdot HV \qquad \forall\, s\in\mathcal{S}, r\in\mathcal{R}, \zeta\in\Phi. \tag{79}$$

$$\sum_{t\in\mathcal{T}} f_{rd}^{t\zeta*}\cdot W_t \le n_{rd}^{\zeta}\cdot CW + h_{rd}^{\zeta}\cdot HW, \sum_{t\in\mathcal{T}} f_{rd}^{t\zeta*}\cdot V_t \le n_{rd}^{\zeta}\cdot CV + h_{rd}^{\zeta}\cdot HV \qquad \forall\, r\in\mathcal{R}, d\in\mathcal{D}, \zeta\in\Phi. \tag{80}$$

$$\sum_{t\in\mathcal{T}} f_{rl}^{t\zeta*}\cdot W_t \le n_{rl}^{\zeta}\cdot CW + h_{rl}^{\zeta}\cdot HW, \sum_{t\in\mathcal{T}} f_{rl}^{t\zeta*}\cdot V_t \le n_{rl}^{\zeta}\cdot CV + h_{rl}^{\zeta}\cdot HV \qquad \forall\, r\in\mathcal{R}, l\in\mathcal{R}, \zeta\in\Phi. \tag{81}$$

where constraints (78)-(81) restrict that the vehicles and helicopters can transport mixed commodities based on the commodity flows obtained in model $\boldsymbol{\mathcal{H}}$ from s to d, from s to r, from r to d, and from r to l, respectively.

6. Case study

This study mainly focuses on two processes, namely (i) multi-commodity rebalancing and (ii) transportation planning. The main concerns on the multi-commodity rebalancing process are quite suitable for rebalancing the medical staff and supplies in COVID-19. However, the main concerns about multi-modal transportation planning with road disruption are the unique features of this study. To validate the effectiveness of the proposed model and approach, a case study of the Yushu Earthquake with road disruption is carried out and the results are reported in this section. The proposed models are implemented in the IBM ILOG CPLEX Optimization Studio (Version: 12.6) with a maximum required computational time (i.e., 300s) so that the globally optimal solution can be obtained in this case study. All the experiments are performed on a computer with an Intel(R) Core(TM) i7-7700 CPU@3.6 GHz and 8 GB memory under Windows 10 Pro system.

6.1. Numerical instance

In this section, a case study of the Yushu Earthquake that measured 7.1 on the surface wave magnitude and occurred in 2010 in Qinghai Province, China is investigated to evaluate the proposed BOSMINP, $\mathcal{A}$, $\mathcal{B}$, $\mathcal{H}$, $\mathcal{F}$ models. The affected area with seismic intensity due to the earthquake is shown in Fig. 4, which is obtained from Ni et al. (2018). For more details about the input parameters, please see the Supplementary Materials.

6.2 Pareto-optimal solutions

In this section, the main results for the MCRT problem are presented. This study first provides the optimal outgoing and incoming shipments at these 13 relief centers with eliminating Ψ_2 (see Fig. 5). With the optimal quantities of outgoing and incoming shipments at relief centers 11-13, the potential demand or supply relief centers can be identified. Specifically, relief-center 11 is considered as a supply point due to the outgoing shipment [see Fig. 5 (a)], whereas relief centers 12 and 13 are considered as demand points when the commodity type of grain is considered. As shown in Fig. 5 (b), relief-center 11 is considered as a demand point, whereas relief centers 12 and 13 are considered as supply points when the commodity type of water is considered. Similarly, relief centers 11-13 are also identified for the commodity types of ration food and medicine [see Fig. 5 (c) and (d)]. It should be noted that relief centers 11-13 are supply and demand points, simultaneously.

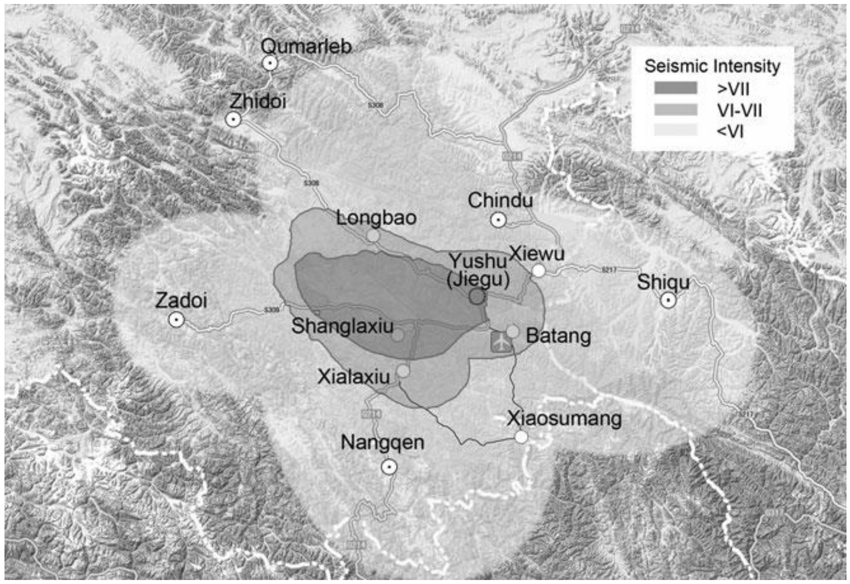
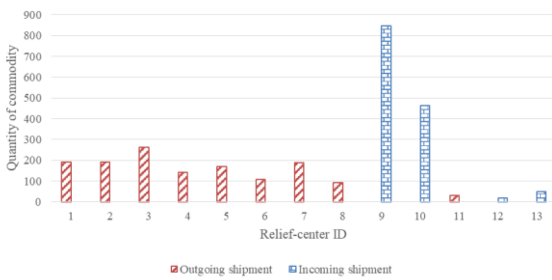
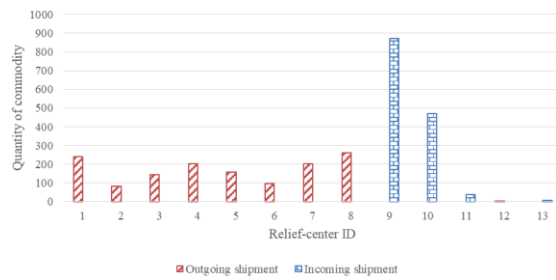


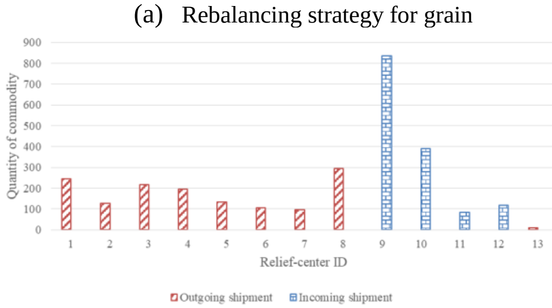
Fig. 4. Seismic intensity map of the affected area



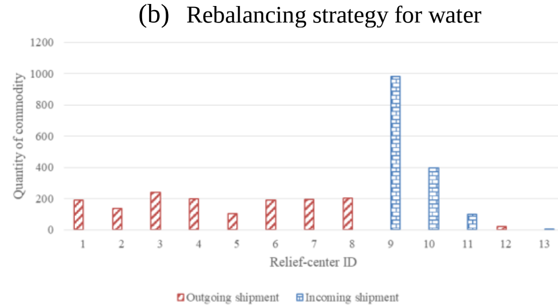
(a) Rebalancing strategy for grain



(b) Rebalancing strategy for water



(c) Rebalancing strategy for ration food



(d) Rebalancing strategy for medicine

Fig. 5. Rebalancing strategy for four commodity types

Based on the realization of the rebalancing strategy, the commodity-flow and transit-related decisions can be determined. The commodity flows are presented in Table 2 and the transit-related decisions are reported in Table 3 for the first scenario. As shown in Table 2, based on the outgoing and incoming shipments, it is obvious that relief centers 11-13 are supply and demand points, simultaneously. Because the roads to the earthquake center (i.e., relief-center 9) are disrupted, only helicopters are used to transport the commodities (see Table 3). Besides, the helicopters choose the long distance and the vehicles select the short distance to deliver commodities.

Table 2 Results of commodity flows between any two relief centers

$\mathcal{S}$ and $\mathcal{R}$	Commodity type	$\mathcal{D}$		$\mathcal{R}$		
		d=9	d=10	r=11	r=12	r=13
s=1	Grain	0	190	0	0	0
	Water	0	204	37	0	0
	Ration food	0	160	85	0	0
	Medicine	0	89	100	0	0
s=2	Grain	175.5	0	0	14.5	0
	Water	70.7	10.3	0	0	0
	Ration food	12	0	0	117	0
	Medicine	139	0	0	0	0
s=3	Grain	79.5	182.5	0	0	0
	Water	0	143	0	0	0
	Ration food	102	114	0	0	0
	Medicine	121	119	0	0	0
s=4	Grain	143	0	0	0	0
	Water	197.3	0	0	0	3.7
	Ration food	195	0	0	0	0
	Medicine	197	0	0	0	0
s=5	Grain	169.5	1.5	0	0	0
	Water	139.6	17.4	0	0	0
	Ration food	135	0	0	0	0
	Medicine	104	0	0	0	0
s=6	Grain	0	57	0	0	50
	Water	0	92.7	0	0	3.3
	Ration food	0	107	0	0	0
	Medicine	0	188	0	0	3
s=7	Grain	186.5	0	0	2.5	0
	Water	201	0	0	0	0
	Ration food	97	0	0	0	0
	Medicine	196	0	0	0	0
s=8	Grain	92	0	0	0	0
	Water	261	0	0	0	0
	Ration food	295	0	0	0	0
	Medicine	203	0	0	0	0
r=11	Grain	0	31	0	0	0
	Water	0	0	0	0	0
	Ration food	0	0	0	0	0
	Medicine	0	0	0	0	0
r=12	Grain	0	0	0	0	0
	Water	1.4	1.6	0	0	0
	Ration food	0	0	0	0	0
	Medicine	21	0	0	0	0
r=13	Grain	0	0	0	0	0
	Water	0	0	0	0	0
	Ration food	0	9	0	0	0
	Medicine	0	0	0	0	0

Table 3 Assigned vehicles and helicopters between relief centers

$\mathcal{S}$ and $\mathcal{R}$	Transit type	$\mathcal{D}$		$\mathcal{R}$		
		d=9	d=10	r=11	r=12	r=13
s=1	Vehicle	0	1	13	0	0
	Helicopter	0	123	0	0	0
s=2	Vehicle	0	0	0	8	0
	Helicopter	75	3	0	0	0

s=3	Vehicle	0	0	0	0	0
	Helicopter	32	103	0	0	0
s=4	Vehicle	0	0	0	0	0
	Helicopter	114	0	0	0	2
s=5	Vehicle	0	4	0	0	0
	Helicopter	99	0	0	0	0
s=6	Vehicle	0	38	0	0	11
	Helicopter	0	0	0	0	0
s=7	Vehicle	0	0	0	0	0
	Helicopter	122	0	0	1	0
s=8	Vehicle	0	0	0	0	0
	Helicopter	124	0	0	0	0
r=11	Vehicle	0	7	0	0	0
	Helicopter	0	0	0	0	0
r=12	Vehicle	0	0	0	0	0
	Helicopter	1	1	0	0	0
r=13	Vehicle	0	1	0	0	0
	Helicopter	0	0	0	0	0

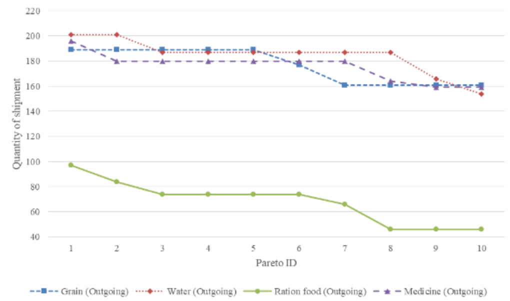
Having obtained the optimal outgoing and incoming shipments with eliminating Ψ_2, the optimal first objective-function value ${\Psi_{1L}}^*$ is considered as the lower-bound value. The total shipment for each commodity type is also obtained and considered as the maximal shipment, which is denoted as ${Max_t}^*$ and given by

$$ {Max_t}^* = \sum_{s\in\mathcal{S}} {o_{ts}}^* + \sum_{r\in\mathcal{R}} {p_{tr}}^* = \sum_{d\in\mathcal{D}} {i_{td}}^* + \sum_{r\in\mathcal{R}} {q_{tr}}^* \qquad \forall\, t \in \mathcal{T}. \tag{82} $$

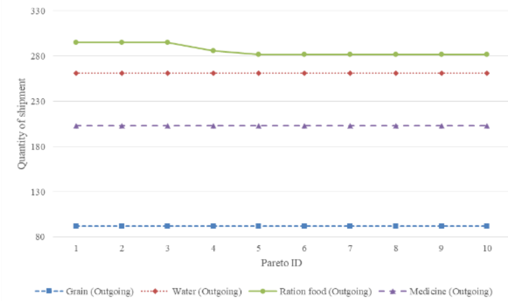
Then the first objective function is converted into a constraint in $\boldsymbol{\mathcal{B}}$ by decreasing the total shipment between relief centers until the minimum total shipment ${Min_t}^*$ is got, which is given by

$$ {Min_t}^* = \max\left\{\sum_{s\in\mathcal{S}} \min_{\xi}\left\{S_{ts} - D_{ts}^{\xi}\right\}, \sum_{d\in\mathcal{D}} \min_{\xi}\left\{D_{td}^{\xi} - S_{td}\right\}\right\} \qquad \forall\, t \in \mathcal{T} \tag{83} $$

Then this study selects ten considerable quantities of shipments from ${Min_t}^*$ to ${Max_t}^*$, which result in ten $\mathcal{E}_1$ values. Given a $\mathcal{E}_1$ value, the outgoing and incoming shipments at relief centers can be obtained. Here two relief centers are selected from each of the three relief-center categories (i.e., 7-12) and the quantities of outgoing and incoming shipments are presented in Figs. 6-8. Specifically, the increase in $\mathcal{E}_1$ value leads to decreasing the quantities of outgoing shipments at supply relief centers 7 and 8 (see Fig. 6). At the same time, it also results in decreasing the quantities of incoming shipments at demand relief centers 9 and 10 (see Fig. 7). As shown in Fig. 8, both the outgoing and incoming shipments are decreasing at relief centers 11 and 12 with an increasing $\mathcal{E}_1$ value, which verifies that relief centers 11 and 12 are supply and demand points simultaneously.

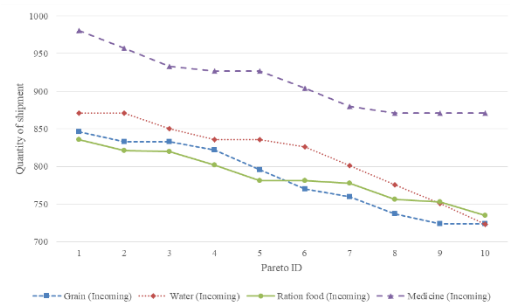


(a) Relief-center 7

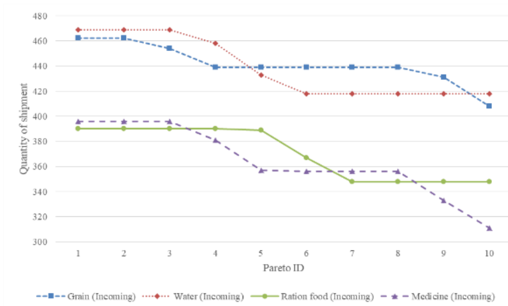


(b) Relief-center 8

Fig. 6. Outgoing shipments at relief centers 7 and 8

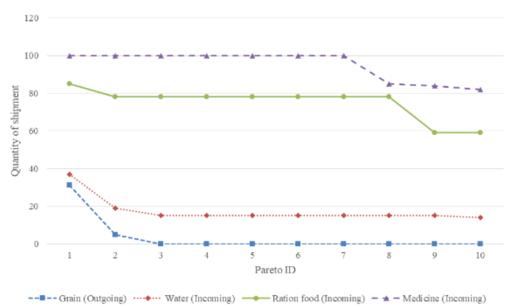


(a) Relief-center 9

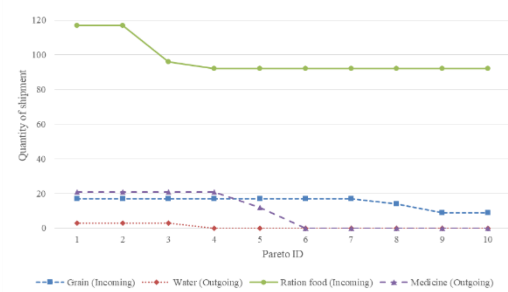


(b) Relief-center 10

Fig. 7. Incoming shipments at relief centers 9 and 10



(a) Relief-center 11



(b) Relief-center 12

Fig. 8. Outgoing and incoming shipments at relief centers 11 and 12

After obtaining the outgoing and incoming shipments given any $\mathcal{E}_1$ value, the second objective function value can be obtained and the commodity-flow and transit-related decision variables are also determined when both AV and AH are 800. Then these Pareto-optimal solutions are presented in Table 4. Compared with vehicles, more helicopters are used to transport commodities to minimize the total transportation time.

Table 4 Optimal Pareto solutions given different $\mathcal{E}_1$ values

Pareto ID	$\mathcal{T}$				$\Psi_1(\mathcal{E}_1)$	Total vehicles		Total helicopters		Ψ_2
	$t1$	$t2$	$t3$	$t4$		$\xi 1$	$\xi 2$	$\xi 1$	$\xi 2$	
1	1,375	1,384	1,428	1,480	28.00	83	81	800	800	1,661.20

2	1,349	1,359	1,406	1,456	28.40	70	70	800	800	1,590.96
3	1,323	1,334	1,384	1,432	29.14	58	58	800	800	1,498.44
4	1,297	1,309	1,362	1,408	30.44	46	46	800	800	1,420.30
5	1,271	1,284	1,340	1,384	32.16	34	34	800	800	1,315.27
6	1,245	1,259	1,318	1,360	34.33	23	23	800	800	1,233.35
7	1,219	1,234	1,296	1,336	36.95	12	12	800	800	1,167.20
8	1,193	1,209	1,274	1,312	40.10	1	1	800	800	1,084.14
9	1,167	1,184	1,252	1,288	44.01	0	0	784	784	1,058.88
10	1,144	1,155	1,234	1,264	48.14	0	0	768	768	1,036.40

Also, a two-dimensional diagram is provided in Fig. 9 to show the visualization of the trade-off between the objective functions, where ten observations are used to construct and identify the set of non-dominated solutions. As depicted in Fig. 9, these two objective functions conflict with each other. Reducing the first objective function value leads to a worsening second objective function value. For the set of non-dominated solutions, none of them can be said to be better than others in the absence of any other information. Thus, additional preference information is needed for the decision-maker to identify the "most preferred" solution.

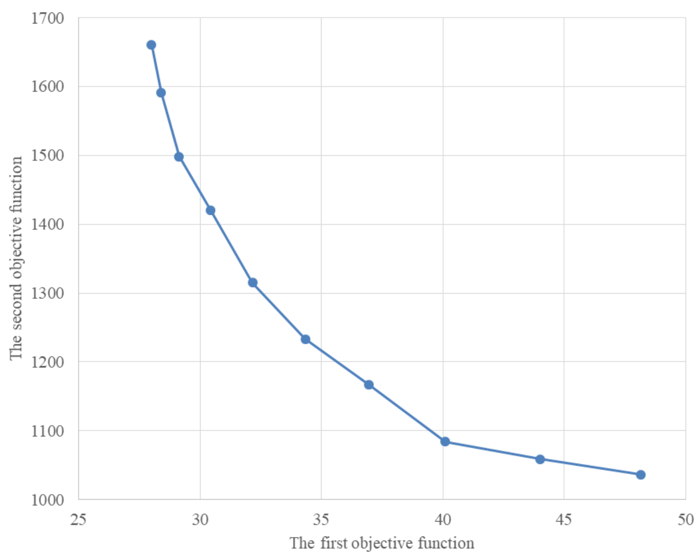


Fig. 9. Trade-off between two objective functions

6.3 Sensitivity analysis

To verify the proposed model and method, sensitivity analysis is conducted to investigate the consequences of varying the critical parameters.

6.3.1 Sensitivity to weights at three relief-center categories

To analyze how the different weights impact the identification of relief centers and outgoing and incoming shipments, three relief centers (i.e., 6, 9, and 12) from three relief-center categories are tested for the commodity of water. As the weight goes from 30 to 80 at relief-center 6, the rebalancing results are presented in Table 5. The quantity of total shipment is becoming smaller. Thus, they have to store more water rather than share water with other demand relief centers. The outgoing shipment of water at relief-center 6 shows a decreasing tendency. Also, the increasing weight of relief-center 6 affects the quantities of outgoing shipments at other relief centers. For instance, relief-center 3 has to share more water (i.e., from 143 to 144) to meet the demand from demand relief centers.

Table 5 Rebalancing results of water given different weights to relief-center 6

Relief center ID	Shipment type	Weight of relief-center 6					
		30	40	50	60	70	80
$s = 1$	Outgoing	241	241	241	241	241	241
$s = 2$	Outgoing	81	81	81	81	81	81
$s = 3$	Outgoing	143	143	143	144	144	144
$s = 4$	Outgoing	201	201	201	201	201	201
$s = 5$	Outgoing	157	157	157	157	157	157
$s = 6$	Outgoing	96	96	96	91	91	91
$s = 7$	Outgoing	201	201	201	201	201	201
$s = 8$	Outgoing	261	261	261	261	261	261
$d = 9$	Incoming	871	871	871	871	871	871
$d = 10$	Incoming	469	469	469	469	469	469
$r = 11$	Outgoing	0	0	0	0	0	0
	Incoming	37	37	37	37	37	37
$r = 12$	Outgoing	3	3	3	3	3	3
	Incoming	0	0	0	0	0	0
$r = 13$	Outgoing	0	0	0	0	0	0
	Incoming	7	7	7	7	3	3
Total shipment		1,384	1,384	1,380	1,380	1,380	1,380

As the weight goes from 30 to 80 at relief-center 9, the rebalancing results are presented in Table 6. The quantity of total shipment is becoming larger. Thus, they need to receive more water from 1384 to 1380 compared with that before. The incoming shipment of water at relief-center 9 shows an increasing tendency from 836 to 871. The growing weight also affects the quantity of outgoing shipment at other supply relief centers. As shown in Table 6, relief centers 3 and 5 have to share more water with the demand relief centers.

Relief-center 12 from the third category is tested when its weight goes from 40 to 80 and the results are reported in Table 7. The increase in the weight of relief-center 12 encourages more shipment from 1384 to 1396 between supply and demand relief centers. Initially, this relief center is considered as a supply point. Then the increase in the weight makes this relief center a demand point. On the contrary, relief-center 13 is considered as a demand point and then a supply point because its weight (priority) is not emphasized anymore compared with that at relief-center 12.

Table 6 Rebalancing results of water given different weights to relief-center 9

Relief-center ID	Shipment type	Weight of relief-center 9				
		60	70	80	90	100
$s = 1$	Outgoing	241	241	241	241	241
$s = 2$	Outgoing	81	81	81	81	81
$s = 3$	Outgoing	132	132	132	143	143
$s = 4$	Outgoing	201	201	201	201	201
$s = 5$	Outgoing	148	148	148	157	157
$s = 6$	Outgoing	96	96	96	96	96
$s = 7$	Outgoing	201	201	201	201	201
$s = 8$	Outgoing	261	261	261	261	261
$d = 9$	Incoming	836	836	836	871	871
$d = 10$	Incoming	484	484	484	469	469
$r = 11$	Outgoing	0	0	0	0	0
	Incoming	37	37	37	37	37
$r = 12$	Outgoing	3	3	3	3	3
	Incoming	0	0	0	0	0
$r = 13$	Outgoing	0	0	0	0	0
	Incoming	7	7	7	7	3
Total shipment		1,364	1,364	1,364	1,384	1,384

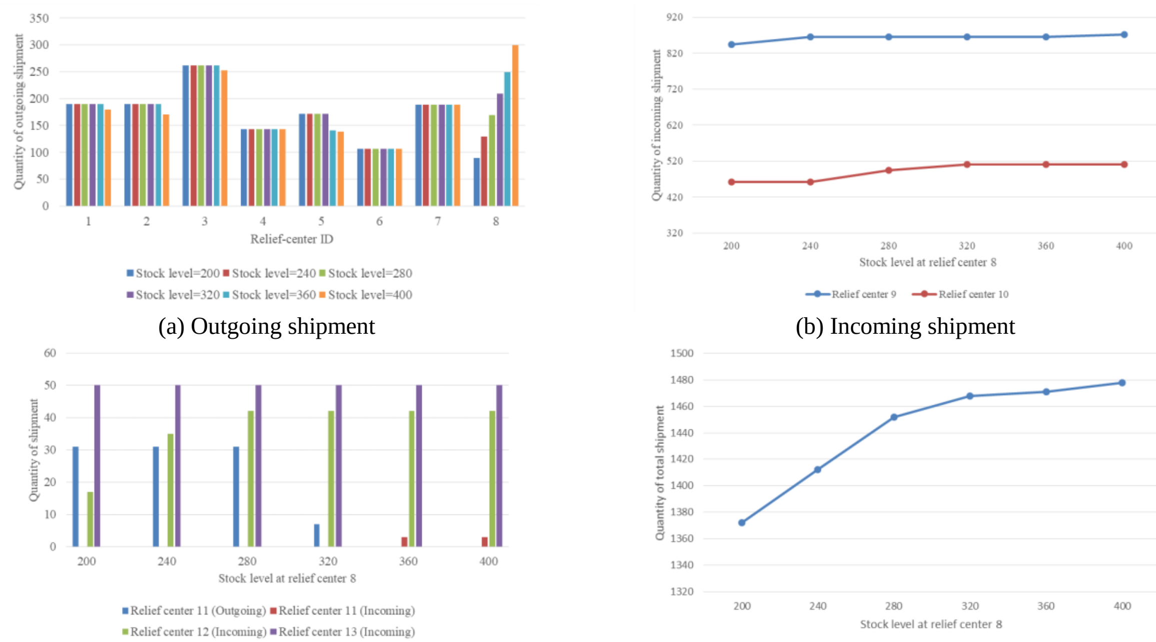
Table 7 Rebalancing results of water given different weights to relief-center 12

Relief-center ID	Shipment type	Weight of relief-center 12				
		40	50	60	70	80
$s = 1$	Outgoing	241	241	241	241	243
$s = 2$	Outgoing	81	81	81	81	81
$s = 3$	Outgoing	143	143	143	144	144
$s = 4$	Outgoing	201	201	201	201	201
$s = 5$	Outgoing	157	157	157	157	157
$s = 6$	Outgoing	96	96	96	96	96
$s = 7$	Outgoing	201	201	201	201	201
$s = 8$	Outgoing	261	261	261	261	261
$d = 9$	Incoming	871	871	871	871	871
$d = 10$	Incoming	469	469	469	469	469
$r = 11$	Outgoing	0	0	0	0	0
	Incoming	37	37	37	37	37
$r = 12$	Outgoing	3	3	3	2	0
	Incoming	0	0	0	0	19
$r = 13$	Outgoing	0	0	0	0	12
	Incoming	7	7	7	7	0
Total shipment		1,384	1,384	1,384	1,384	1,396

6.3.2 Sensitivity to stock levels at three relief-center categories

The stock levels at relief centers also have a great influence on the identification of relief centers and outgoing and incoming shipments. Three relief centers (i.e., 8, 10, and 12) from three different relief-center categories are tested for grain, respectively.

The outgoing and incoming shipments of grain at all relief centers and the total shipment of grain are shown in Fig. 10 with the stock level at relief-center 8 from 200 to 400. On the whole, the total shipment of grain is increasing as the stock level at relief-center 8 goes from 200 to 400 [see Fig. 10(d)]. In particular, given a higher stock level of grain at relief-center 8, this relief center can share more grain with other demand relief centers and other supply relief centers (i.e., 2, 3, and 5) do not need to share too much grain anymore [see Fig. 10(a)]. As shown in Fig. 10(b), both relief centers 9 and 10 have higher incoming shipments of grain as the stock level goes from 200 and 400. Besides, the incoming shipment of grain at relief-center 12 begins to increase due to its high priority and low stock level [see Fig. 10(c)]. Also, it should be noted that relief-center 11 starts to receive grain and changes to a demand point when the stock level goes from 320 and 360.

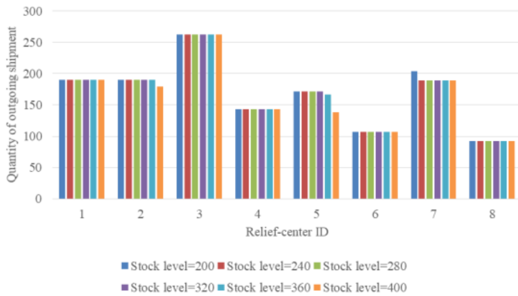


(a) Outgoing shipment (b) Incoming shipment

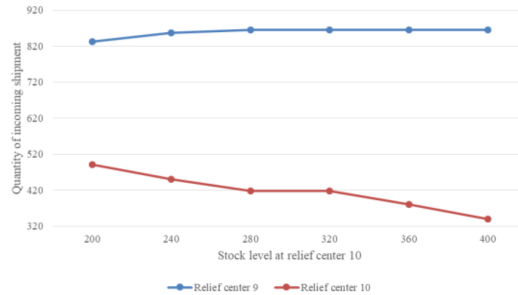
(c) Outgoing and incoming shipments (d) Total shipment

Fig. 10. Rebalancing results of grain under different stock levels at relief-center 8

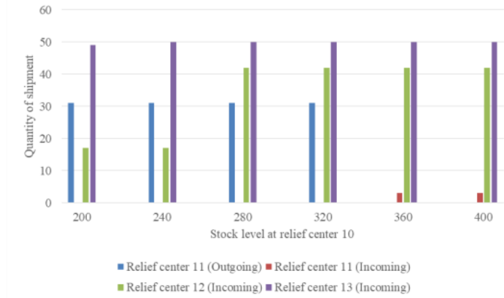
Then relief-center 10 belonging to the demand relief-center category is used to test the influences of different stock levels. Overall, the increasing stock level at relief-center 10 results in a decreasing total shipment of grain [see Fig. 11(d)]. Specifically, supply relief centers have no need to share too much grain anymore, which makes the outgoing shipments decrease at relief centers 2, 5, and 7 [see Fig. 11(a)]. As shown in Fig. 11(b), the incoming shipment of grain increases at relief-center 9, whereas the incoming shipment of grain decreases at relief-center 10 as the stock level goes from 200 to 400. Also, a higher stock level at relief-center 10 leads to increasing demand at relief centers 11-13. Interestingly, relief-center 11 is initially identified as a supply point. However, as the stock level increases, relief-center 11 changes to a demand point and begins to receive grain [see Fig. 11(c)].



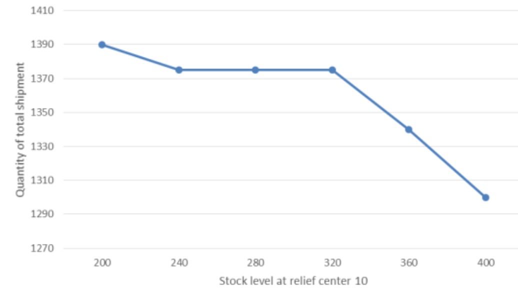
(a) Outgoing shipment



(b) Incoming shipment



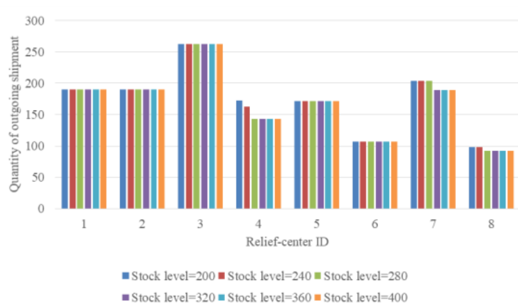
(c) Outgoing and incoming shipments



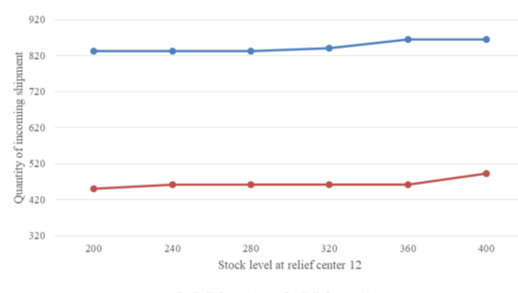
(d) Total shipment

Fig. 11. Rebalancing results for grain under different stock levels at relief-center 10

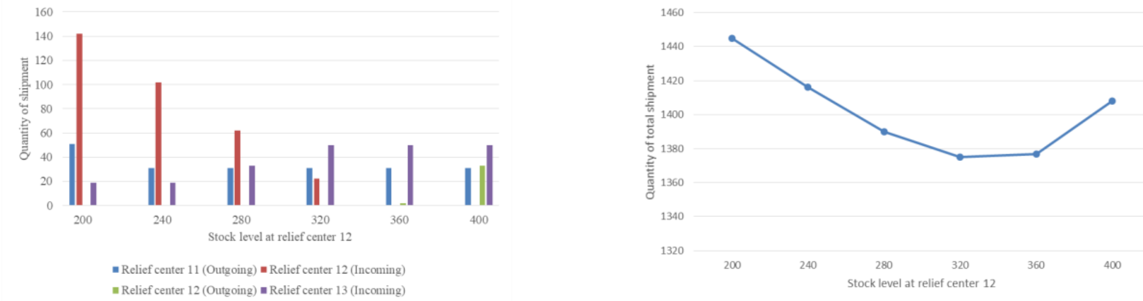
In the end, this study investigates the consequences of changes in the stock level at relief-center 12 belonging to the third category. With the stock level from 200 to 400, the rebalancing results for grain are presented in Fig. 12. Firstly, the supply relief centers (i.e., 4, 7, and 8) do not need to share too much grain with the other two relief-center categories [see Fig. 12(a)]. Secondly, as shown in Fig. 12(b), the demand relief centers (i.e., 9 and 10) have more incoming shipments. For the third category of relief centers, initially, relief-center 11 is considered as a supply point, whereas relief centers 12 and 13 are considered as demand points. Noted that relief-center 12 changes to a supply point when its stock level goes from 320 to 360. Finally, since the stock level of grain grows from 200 to 320 at relief-center 12, the total shipment of grain decreases. However, as the stock level goes from 320 to 400, the total shipment of grain begins to increase, and relief-center 12 changes to a supply point and encourages more shipment of grain between supply and demand relief centers.



(a) Outgoing shipment



(b) Incoming shipment



(c) Outgoing and incoming shipments (d) Total shipment

Fig. 12 Rebalancing results for grain under different stock levels at relief-center 12

6.3.3 Sensitivity to road disruption and availability

As road disruption and road availability are important factors that delay humanitarian logistics and contribute to increasing delivery times, it is critical to investigate their impacts on the total transportation time. The sensitivity analysis is conducted based on a crossover trial for the above two factors, where each of the factors has two levels. Then there are 2×2 treatment combinations in total, which are Combinations (I)-(IV) and reported in Table 8. With the outgoing and incoming shipments at all relief centers, the commodity-flow and transit-related decisions from different treatment combinations are obtained and compared. Note that the Combinations (I) and (III) consider the road availability in the second scenario. And the results of Combination (I) have been presented in Subsection 6.2. Because of too many decision variables in terms of commodity-flow and transit-related decisions, this study only shows the total outgoing and incoming shipments among three relief-center categories for the first set of Pareto-optimal solutions in Table 9. And the total numbers of vehicles and helicopters are presented in Figs. 13 and 14, respectively.

Table 8 Four treatment combinations in the crossover trial

Combinations	Road availability	None road availability
Road disruption	Combination (I)	Combination (II)
None road disruption	Combination (III)	Combination (IV)

As shown in Table 9, it is obvious that the total outgoing and incoming shipments among relief-center categories are influenced by road disruption and availability. To be more specific, for the commodity of water (i.e., $t=2$), the total shipment from the category $\mathcal{S}$ to the category $\mathcal{D}$ is 1340 in Combination (I), which is different from that (i.e., 1337) in Combinations (II)-(IV). Obviously, it proves that either road disruption or road availability can affect the commodity flows between relief centers.

Table 9 Total outgoing and incoming shipments among relief-center categories

Combination ID	Relief-center Category	$\mathcal{T}$							
		$t=1$		$t=2$		$t=3$		$t=4$	
		$\mathcal{D}$	$\mathcal{R}$	$\mathcal{D}$	$\mathcal{R}$	$\mathcal{D}$	$\mathcal{R}$	$\mathcal{D}$	$\mathcal{R}$
I	$\mathcal{S}$	1,277	67	1,340	41	1,217	202	1,356	103

	$\mathcal{R}$	31	0	0	3	9	0	21	0
II	$\mathcal{S}$	1,277	67	1,337	44	1,217	202	1,356	103
	$\mathcal{R}$	31	0	3	0	9	0	21	0
III	$\mathcal{S}$	1,277	67	1,337	44	1,217	202	1,356	103
	$\mathcal{R}$	31	0	3	0	9	0	21	0
IV	$\mathcal{S}$	1,277	67	1,337	44	1,217	202	1,356	103
	$\mathcal{R}$	31	0	3	0	9	0	21	0

As shown in Fig. 13, with the Pareto ID from 1 to 10, fewer vehicles are used. Specifically, the minimum number of vehicles are used in Combination (I) with the consideration of road disruption and availability. However, in Combination (II) with the consideration of road disruption only, the number of vehicles is larger than that in Combination (I). The reason is that even though the speed of the vehicle is much slower than that of the helicopter, the shorter loading/unloading time and higher volume and weight capacities encourage the vehicle to provide relatively quick delivery when the distance is short. Besides, when road disruption is considered in Combination (III), the number of vehicles also increases. Furthermore, in Combination (IV) without considering the road disruption and availability, the number of vehicles is further increased as the vehicles take a shorter time to transport commodities compared with the helicopters. Nevertheless, as shown in Fig. 14, the number of helicopters presents an opposite trend compared with the number of vehicles in Combinations (I)-(IV).

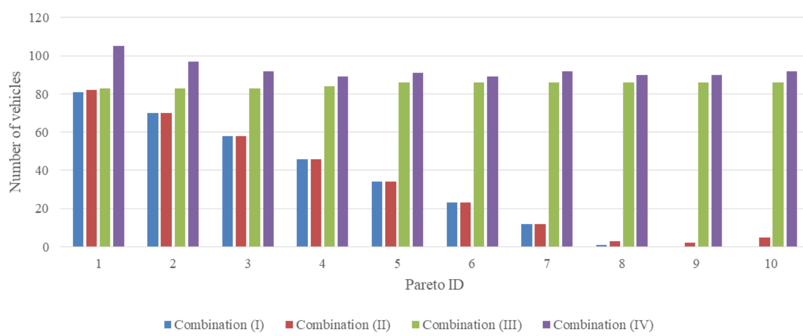


Fig. 13. Number of vehicles in four treatment combinations

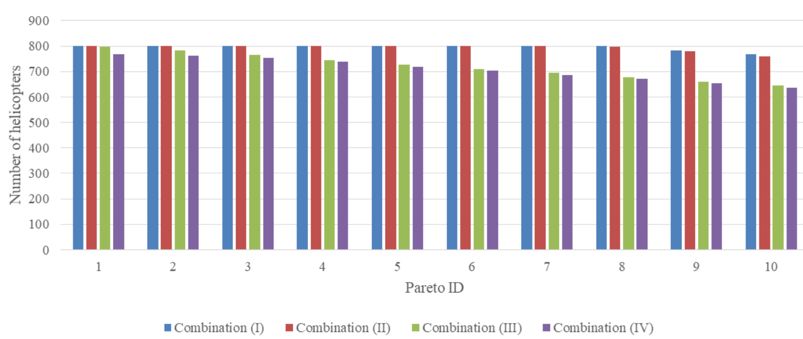


Fig. 14. Number of helicopters in four treatment combinations

Also, this study provides the trade-off between the two objective functions for four treatment combinations in Fig. 15. It is obvious that these two objective functions conflict with each other in each of the Combinations (I)-(IV). Besides, the ten observations for Combination (IV) are better than the corresponding observations in Combinations (I)-(III) because both objective function values in Combination (IV) are smaller than the corresponding values in Combinations (I)-(III). It also verifies that the vehicles can save transportation time on shorter routes of good conditions compared with the helicopters (see Figs. 13-15). Thus, the decision-makers need to assign these vehicles and helicopters reasonably to transport commodities among relief centers.

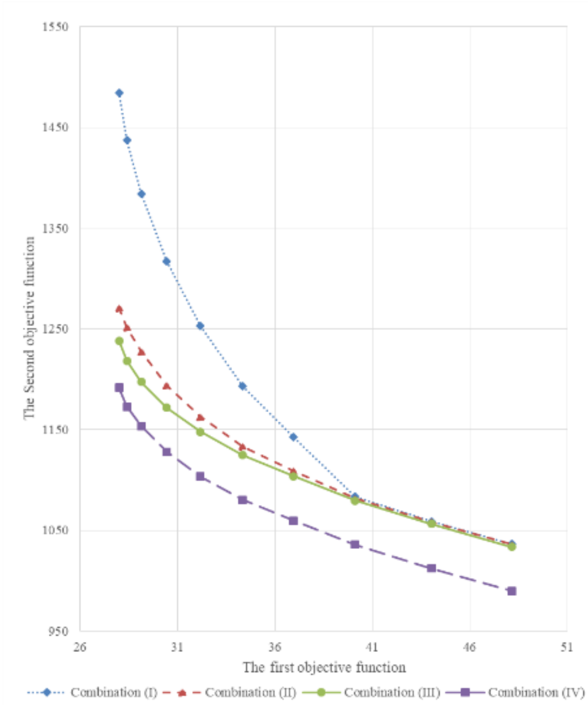


Fig. 15. Trade-off between the two objective functions in four treatment combinations

6.3.4 Sensitivity to different problem sizes

The last parameter to undergo sensitivity analysis is the problem size. As presented in Subsection 6.2, the proposed model $\mathcal{B}$ is solvable given the present problem with four commodity types. However, when too many relief centers or commodity types are involved, it is impossible to obtain the optimal solution for the second objective function within a reasonable computation time. Then the proposed models $\mathcal{H}$ and $\mathcal{F}$ need to be used to determine some not bad solutions. In this sense, this study tests the solution performances for 12 different problem sizes reported in Table 10. To construct those different problems, this study applies the same method to generate the parameters at relief centers. The numbers of relief centers from three different categories in the third instance are the same as the case study. Besides, the same maximum required computational time (i.e., 300s) in the case study is also considered as a baseline to test the problems of different sizes in this subsection.

Table 10 Instances of different problem sizes

Instance ID	$\mathcal{S}$	$\mathcal{D}$	$\mathcal{R}$	$\mathcal{T}$
1	8	2	3	2
2	8	2	3	3
3	8	2	3	4
4	13	4	6	2
5	13	4	6	3
6	13	4	6	4
7	18	6	9	2
8	18	6	9	3
9	18	6	9	4
10	23	8	12	2
11	23	8	12	3
12	23	8	12	4

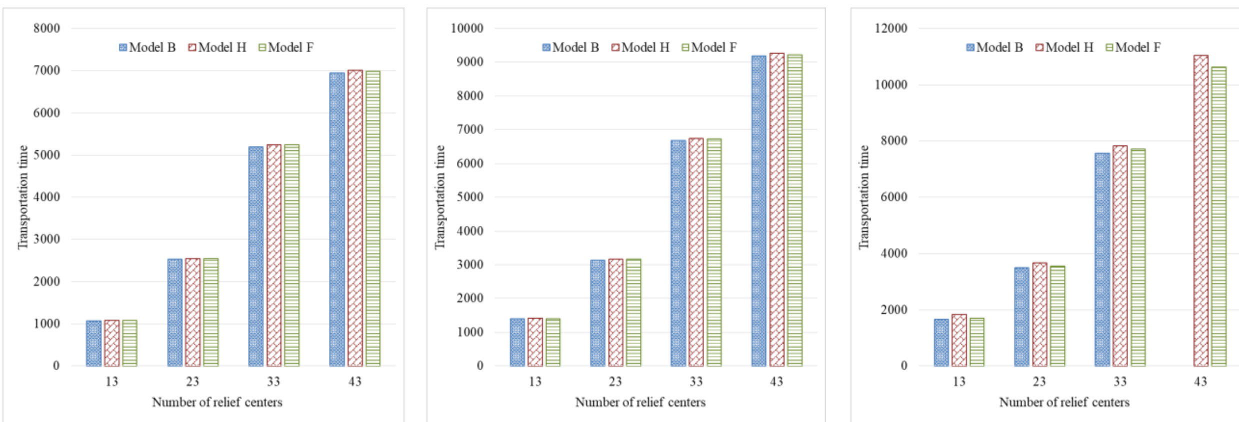
Based on the above 12 instances, this study implements the proposed three models, $\boldsymbol{\mathcal{B}}$, $\boldsymbol{\mathcal{H}}$, and $\boldsymbol{\mathcal{F}}$ in the CPLEX and presents the partial Pareto-optimal solutions with the Gaps in Table 11 within 300s. And this study also shows the comparison results of objective function values using models $\boldsymbol{\mathcal{B}}$, $\boldsymbol{\mathcal{H}}$, and $\boldsymbol{\mathcal{F}}$ in Fig. 16. As presented in Table 11, fewer vehicles and helicopters are obtained in models $\boldsymbol{\mathcal{B}}$ and $\boldsymbol{\mathcal{F}}$ compared with that in model $\boldsymbol{\mathcal{H}}$. As the helicopter has a higher speed, the helicopters dominant the transportation of commodities. Besides, it is obvious that the model $\boldsymbol{\mathcal{B}}$ has the smallest objective function value compared with that in models $\boldsymbol{\mathcal{H}}$, and $\boldsymbol{\mathcal{F}}$. However, the increasing problem size makes the model $\boldsymbol{\mathcal{B}}$ more difficult to solve. The Gap in model $\boldsymbol{\mathcal{B}}$ begins to incease and finally the model $\boldsymbol{\mathcal{B}}$ ends with "out of memory" (see Instance 12 in Table 11). Nevertheless, the combination of models $\boldsymbol{\mathcal{B}}$ and $\boldsymbol{\mathcal{F}}$ is still solvable when the problem size is getting larger, which verifies the efficiency of the proposed approach. As depicted in Fig. 16, the objective function values obtained in models $\boldsymbol{\mathcal{B}}$ and $\boldsymbol{\mathcal{F}}$ are very close to each other, indicating that the solution through model $\boldsymbol{\mathcal{F}}$ can be obtain using shorter time without losing a big generosity.

Table 11 Results of different-sized problems

Instance ID	AV/AH	Model	$\boldsymbol{\mathcal{B}}$			$\boldsymbol{\mathcal{H}}$		$\boldsymbol{\mathcal{F}}$	
		$\boldsymbol{\Phi}$	NV	NH	Gaps	NV	NH	NV	NH
1		$\zeta = 1$	0	792	0	0	795	0	794
		$\zeta = 2$	0	792		0	795	0	795
2	800	$\zeta = 1$	53	800	0	56	800	54	800
		$\zeta = 2$	51	800		54	800	52	800
3		$\zeta = 1$	83	800	0	98	800	86	800
		$\zeta = 2$	81	800		94	800	85	800
4		$\zeta = 1$	137	1,300	0.13%	138	1,300	137	1,300
		$\zeta = 2$	138	1,300		139	1,300	139	1,300
5	1,300	$\zeta = 1$	244	1,300	0.40%	249	1,300	248	1,300
		$\zeta = 2$	246	1,300		249	1,300	248	1,300
6		$\zeta = 1$	304	1,300	0.61%	332	1,300	310	1,300

		$\zeta = 2$	304	1,300		331	1,300	312	1,300
7		$\zeta = 1$	283	1,800	0.29%	283	1,800	283	1,300
		$\zeta = 2$	284	1,800		286	1,800	286	1,300
8	1,800	$\zeta = 1$	442	1,800	0.78%	446	1,800	445	1,300
		$\zeta = 2$	442	1,800		450	1,800	447	1,300
9		$\zeta = 1$	531	1,800	1.46%	562	1,800	539	1,800
		$\zeta = 2$	531	1,800		563	1,800	537	1,800
10		$\zeta = 1$	334	2,300	0.23%	340	2,300	339	2,300
		$\zeta = 2$	335	2,300		339	2,300	337	2,300
11	2,300	$\zeta = 1$	534	2,300	1.56%	542	2,300	541	2,300
		$\zeta = 2$	532	2,300		543	2,300	538	2,300
12		$\zeta = 1$	Out of memory			687	2,300	655	2,300
		$\zeta = 2$				688	2,300	654	2,300

NV: Total number of vehicles; NH: Total number of helicopters.



(a) Two commodity types (b) Three commodity types (c) Four commodity types

Fig. 16. Objective function values in models $\boldsymbol{\mathcal{B}}$, $\boldsymbol{\mathcal{H}}$, and $\boldsymbol{\mathcal{F}}$ of different problem sizes

7. Conclusions

This study, as an explorative study, investigated the MCRT planning over a multi-modal transportation network with combined distances in disaster response. Then a BOSMINP model was proposed to formulate the problem and address various non-negligible issues including fairness, uncertainty, road damage and disruption, and different transportation means. In the proposed BOSMINP model, two objectives were considered, namely, maximization of fairness by minimizing the expected total weighted proportion of unmet demand, and minimization of the expected total transportation time. The strategic decisions of the model involve: (i) relief-center identification; (ii) incoming and outgoing shipments; (iii) commodity flows; (iv) number of required vehicles; and (v) number of required helicopters. Due to the nonlinearity of the proposed BOSMINP model, a linearization approach was further introduced. Then an adaptive $\mathcal{E}$-constraint method was applied to solve the proposed bi-objective model so that a set of non-dominated solutions could be obtained. However, the linearized model is still difficult to solve as the problem size becomes larger. To overcome the above difficulty, the model was reformulated to obtain an upper bound for the second objective function before the optimal solution is determined. In the end, a case study of the great Yushu Earthquake in China was implemented to validate the proposed model and approach. The trade-off between the conflicting objectives was obtained with sensitivity analysis of several key parameters, which illustrates the effectiveness of the decision-making in the MCRT planning in disaster response. Furthermore, some deep managerial implications were drawn from the case study, which provides the main needs and benefits of this study. Particularly, the main managerial insights for the researchers and managers are outlined as follows:

(1) Rebalancing the commodities is quite imperative to maximize fairness. As presented in Fig. 5, the incoming and outgoing shipments are positive at relief centers, which indicates that the previous multi-commodity preparedness is unbalanced. In this sense, rebalancing the commodities is quite imperative. After the COVID-19, the medical staff and supplies also need to be rebalanced due to the dissimilarly and unevenly distributed prevalence of infection, which results in an imbalance of supply to demand. In such a case, the proposed model in this study is also suitable for rebalancing the medical staff and supplies in response to COVID-19.

(2) Through the sensitivity analysis to road disruption and availability, it is found that recovering the disrupted roads is meaningful because there is a positive correlation between the number of vehicles and road conditions. Particularly, vehicles can reduce transportation time on shorter routes of good conditions. Although the helicopters dominate the transportation of commodities due to the extremely high speed, it is still meaningful to recover the disrupted roads so that more vehicles are used to transport commodities on some shorter routes and further reduce the total transportation time.

(3) This study also reveals that either weight or stock level affects the decision variables that include the outgoing shipment, incoming shipment, and relief-center identification. In this sense, it is better to prepare or distribute more commodities in the relief centers with higher potential disaster severities (weights) so that the demand and supply can be well matched.

Despite the above novelties and contributions, this work still has several limitations. It may not be able to find the optimal solution when the problem size is extremely large. Besides, this study only explores the issue of single-period MCRT planning over the multi-modal transportation network. Also, traffic congestion for vehicles is not considered in this study. Therefore, potential future research works can be done to: i) propose the corresponding metaheuristic method to solve the large-sized problems; ii) provide a cyclic rolling horizon-based updating framework to construct a reliable multi-period MCRT planning in disaster response; iii) include some other indexes in the analysis, such as traffic congestion for vehicles; and iv) focus on rebalancing the medical staff and supplies in response to COVID-19.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (71861167002, 5183000192) and the National Research Foundation of Korea (NRF) grant funded by the Korea government (NRF-2017R1A2B4004169).

References

Alumur, S.A., B.Y. Kara, and O.E. Karasan. (2012). Multimodal hub location and hub network design, Omega. 40 (6), 927-939.

Arnette, A.N., and C.W. Zobel. (2019). A Risk‐Based Approach to Improving Disaster Relief Asset Pre‐Positioning, Production and Operations Management. 28 (2), 457-478.

Bababeik, M., N. Khademi, and A. Chen. (2018). Increasing the resilience level of a vulnerable rail network: The strategy of location and allocation of emergency relief trains, Transportation Research Part E: Logistics and Transportation Review. 119, 110-128.

Baharmand, H., T. Comes, and M. Lauras. (2019). Bi-objective multi-layer location–allocation model for the immediate aftermath of sudden-onset disasters, Transportation Research Part E: Logistics and Transportation Review. 127, 86-110.

Bai, X., (2016). Two-stage multiobjective optimization for emergency supplies allocation problem under integrated uncertainty, Mathematical Problems in Engineering. 2016.

Balcik, B., S. Silvestri, M.È. Rancourt, and G. Laporte. (2019). Collaborative Prepositioning Network Design for Regional Disaster Response, Production and Operations Management. 28 (10), 2431-2455.

Balcik, B., and İ. Yanıkoğlu. (2020). A robust optimization approach for humanitarian needs assessment planning under travel time uncertainty, European Journal of Operational Research. 282 (1), 40-57.

Bozorgi-Amiri, A., M. Jabalameli, and S.M. Al-e-Hashem. (2013). A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty, OR Spectrum. 35 (4), 905-933.

Camacho-Vallejo, J.-F., E. González-Rodríguez, F.-J. Almaguer, and R.G. González-Ramírez. (2015). A bi-level optimization model for aid distribution after the occurrence of a disaster, Journal of Cleaner Production. 105, 134-145.

Cao, C., C. Li, Q. Yang, Y. Liu, and T. Qu. (2018). A novel multi-objective programming model of relief distribution for sustainable disaster supply chain in large-scale natural disasters, Journal of Cleaner Production. 174, 1422-1435.

Cao, M.-T., Q.-V. Tran, N.-M. Nguyen, and K.-T. Chang. (2020). Survey on performance of deep learning models for detecting road damages using multiple dashcam image resources, Advanced Engineering Informatics. 46, 101182.

Cavdur, F., M. Kose-Kucuk, and A. Sebatli. (2016). Allocation of temporary disaster response facilities under demand uncertainty: An earthquake case study, International Journal of Disaster Risk Reduction. 19, 159-166.

Chen, A.Y., and T.-Y. Yu. (2016). Network based temporary facility location for the Emergency Medical Services considering the disaster induced demand and the transportation infrastructure in disaster response, Transportation Research Part B: Methodological. 91, 408-423.

Dai, R., and H. Charkhgard. (2017). A two-stage approach for bi-objective integer linear programming, Operations Research Letters.

Davis, L.B., F. Samanlioglu, X. Qu, and S. Root. (2013). Inventory planning and coordination in disaster relief efforts, International Journal of Production Economics. 141 (2), 561-573.

Döyen, A., N. Aras, and G. Barbarosoğlu. (2012). A two-echelon stochastic facility location model for humanitarian relief logistics, Optimization Letters. 6 (6), 1123-1145.

Elci, O., and N. Noyan. (2018). A chance-constrained two-stage stochastic programming model for humanitarian relief network design, Transportation Research Part B-Methodological. 108, 55-83.

Emanuel, E.J., G. Persad, R. Upshur, B. Thome, M. Parker, A. Glickman, C. Zhang, C. Boyle, M. Smith, and J.P. Phillips. (2020). Fair allocation of scarce medical resources in the time of Covid-19. In.: Mass Medical Soc.

Erbeyoğlu, G., and Ü. Bilge. (2020). A robust disaster preparedness model for effective and fair disaster response, European Journal of Operational Research. 280 (2), 479-494.

Gao, X. (2019). A stochastic optimization model for commodity rebalancing under traffic congestion in disaster response. In *IFIP international conference on advances in production management systems*, 91-99. Springer.

Gao, X., (2020). A bi-level stochastic optimization model for multi-commodity rebalancing under uncertainty in disaster response, Annals of Operations Research, 1-34.

Gao, X., and C. Cao. (2020). Multi-commodity rebalancing and transportation planning considering traffic congestion and uncertainties in disaster response, Computers & Industrial Engineering, 106782.

Gao, X., and X. Jin. (2020). A Robust Multi-commodity Rebalancing Process in Humanitarian Logistics. In *IFIP International Conference on Advances in Production Management Systems*, 3-10. Springer.

Gao, X., and G.M. Lee. (2018). A Stochastic Programming Model for Multi-commodity Redistribution Planning in Disaster Response. In *IFIP International Conference on Advances in Production Management Systems*, 67-78. Springer.

Gao, X., M.K. Nayeem, and I.M. Hezam. (2019). A robust two-stage transit-based evacuation model for large-scale disaster response, Measurement. 145, 713-723.

Gao, X., Y. Zhou, M.I.H. Amir, F.A. Rosyidah, and G.M. Lee. (2017). A Hybrid Genetic Algorithm For Multi-emergency Medical Service Center Location-allocation Problem In Disaster Response, International Journal of Industrial Engineering. 24 (6).

Gillani, A.H., M.I. Mohamed Ibrahim, J. Akbar, and Y. Fang. (2020). Evaluation of Disaster Medicine Preparedness among Healthcare Profession Students: A Cross-Sectional Study in Pakistan, International Journal of Environmental Research and Public Health. 17 (6), 2027.

Guha-Sapir, D., F. Vos, R. Below, and S. Ponserre. (2012). Annual disaster statistical review 2011: the numbers and trends. In.: Centre for Research on the Epidemiology of Disasters (CRED).

Gutjahr, W.J., and N. Dzubur. (2016). Bi-objective bilevel optimization of distribution center locations considering user equilibria, Transportation Research Part E: Logistics and Transportation Review. 85, 1-22.

Haddow, G., J. Bullock, and D.P. Coppola. (2017). *Introduction to emergency management* (Butterworth-Heinemann).

Haghi, M., S.M.T.F. Ghomi, and F. Jolai. (2017). Developing a robust multi-objective model for pre/post disaster times under uncertainty in demand and resource, Journal of Cleaner Production. 154, 188-202.

Haimes, Y.Y., (1971). On a bicriterion formulation of the problems of integrated system identification and system optimization, IEEE transactions on systems, man, and cybernetics. 1 (3), 296-297.

Holguín-Veras, J., N. Pérez, M. Jaller, L.N. Van Wassenhove, and F. Aros-Vera. (2013). On the appropriate objective function for post-disaster humanitarian logistics models, Journal of Operations Management. 31 (5), 262-280.

Hong, X., M.A. Lejeune, and N. Noyan. (2015). Stochastic network design for disaster preparedness, IIE Transactions. 47 (4), 329-357.

Hu, D., S. Li, J. Chen, and V.R. Kamat. (2019). Detecting, locating, and characterizing voids in disaster rubble for search and rescue, Advanced Engineering Informatics. 42, 100974.

Huang, K., Y. Jiang, Y. Yuan, and L. Zhao. (2015). Modeling multiple humanitarian objectives in emergency response to large-scale disasters, Transportation Research Part E: Logistics and Transportation Review. 75, 1-17.

Ishfaq, R., and C.R. Sox. (2011). Hub location–allocation in intermodal logistic networks, European Journal of Operational Research. 210 (2), 213-230.

Jung, D., V. Tran Tuan, Q. Dai Tran, M. Park, and S. Park. (2020). Conceptual Framework of an Intelligent Decision Support System for Smart City Disaster Management, Applied Sciences. 10 (2), 666.

Kostoulas, D., R. Aldunate, F.P. Mora, and S. Lakhera. (2008). A nature-inspired decentralized trust model to reduce information unreliability in complex disaster relief operations, Advanced Engineering Informatics. 22 (1), 45-58.

Li, C., F. Zhang, C. Cao, Y. Liu, and T. Qu. (2019). Organizational coordination in sustainable humanitarian supply chain: An evolutionary game approach, Journal of cleaner production. 219, 291-303.

Li, L., M. Jin, and L. Zhang. (2011). Sheltering network planning and management with a case in the Gulf Coast region, International Journal of Production Economics. 131 (2), 431-440.

Li, M., P. Lin, G. Xu, and G.Q. Huang. (2018). Cloud-based ubiquitous object sharing platform for heterogeneous logistics system integration, Advanced Engineering Informatics. 38, 343-356.

Lin, Y.-H., R. Batta, P.A. Rogerson, A. Blatt, and M. Flanigan. (2011). A logistics model for emergency supply of critical items in the aftermath of a disaster, Socio-Economic Planning Sciences. 45 (4), 132-145.

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

Loree, N., and F. Aros-Vera. (2018). Points of distribution location and inventory management model for Post-Disaster Humanitarian Logistics, Transportation Research Part E: Logistics and Transportation Review. 116, 1-24.

Lu, S., L. Zhu, Y. Wang, L. Xie, and H. Su. (2020). Integrated forward and reverse logistics network design for a hybrid assembly-recycling system under uncertain return and waste flows: A fuzzy multi-objective programming, Journal of Cleaner Production. 243, 118591.

Mavrotas, G., (2009). Effective implementation of the ε-constraint method in multi-objective mathematical programming problems, Applied mathematics and computation. 213 (2), 455-465.

Meraklı, M., and H. Yaman. (2016). Robust intermodal hub location under polyhedral demand uncertainty, Transportation Research Part B: Methodological. 86, 66-85.

Mete, H.O., and Z.B. Zabinsky. (2010). Stochastic optimization of medical supply location and distribution in disaster management, International Journal of Production Economics. 126 (1), 76-84.

Mills, A.F., N.T. Argon, and S. Ziya. (2018). Dynamic Distribution of Patients to Medical Facilities in the Aftermath of a Disaster, Operations Research. 66 (3), 716-732.

Mohamadi, A., and S. Yaghoubi. (2017). A bi-objective stochastic model for emergency medical services network design with backup services for disasters under disruptions: An earthquake case study, International Journal of Disaster Risk Reduction. 23, 204-217.

Mohammadi, R., S.F. Ghomi, and F. Jolai. (2016). Prepositioning emergency earthquake response supplies: A new multi-objective particle swarm optimization algorithm, Applied Mathematical Modelling. 40 (9), 5183-5199.

Moreno, A., D. Alem, and D. Ferreira. (2016). Heuristic approaches for the multiperiod location-transportation problem with reuse of vehicles in emergency logistics, Computers & Operations Research. 69, 79-96.

Ni, W., J. Shu, and M. Song. (2018). Location and Emergency Inventory Pre‐Positioning for Disaster Response Operations: Min‐Max Robust Model and a Case Study of Yushu Earthquake, Production and Operations Management. 27 (1), 160-183.

Park, S., S.H. Park, L.W. Park, S. Park, S. Lee, T. Lee, S.H. Lee, H. Jang, S.M. Kim, and H. Chang. (2018). Design and implementation of a smart IoT based building and town disaster management system in smart city infrastructure, Applied Sciences. 8 (11), 2239.

Paul, J.A., and M. Zhang. (2019). Supply location and transportation planning for hurricanes: A two-stage stochastic programming framework, European Journal of Operational Research. 274 (1), 108-125.

Pi, Y., N.D. Nath, and A.H. Behzadan. (2020). Convolutional neural networks for object detection in aerial imagery for disaster response and recovery, Advanced Engineering Informatics. 43, 101009.

Rath, S., M. Gendreau, and W.J. Gutjahr. (2016). Bi‐objective stochastic programming models for determining depot locations in disaster relief operations, International Transactions in Operational Research. 23 (6), 997-1023.

Rawls, C.G., and M.A. Turnquist. (2010). Pre-positioning of emergency supplies for disaster response, Transportation research part B: Methodological. 44 (4), 521-534.

Rennemo, S.J., K.F. Rø, L.M. Hvattum, and G. Tirado. (2014). A three-stage stochastic facility routing model for disaster response planning, Transportation research part E: logistics and transportation review. 62, 116-135.

Rivera-Royero, D., G. Galindo, and R. Yie-Pinedo. (2016). A dynamic model for disaster response considering prioritized demand points, Socio-economic planning sciences. 55, 59-75.

Rodríguez-Espíndola, O., P. Albores, and C. Brewster. (2018). Dynamic formulation for humanitarian response operations incorporating multiple organisations, International Journal of Production Economics. 204, 83-98.

Ronke, P., (2018). Natural catastrophes and man-made disasters in 2017: A year of record-breaking losses, Sigma. 22.

Rottkemper, B., K. Fischer, and A. Blecken. (2012). A transshipment model for distribution and inventory relocation under uncertainty in humanitarian operations, Socio-Economic Planning Sciences. 46 (1), 98-109.

Safaei, A.S., S. Farsad, and M.M. Paydar. (2018). Robust bi-level optimization of relief logistics operations, Applied Mathematical Modelling. 56, 359-380.

Song, J.M., W. Chen, and L. Lei. (2018). Supply chain flexibility and operations optimisation under demand uncertainty: a case in disaster relief, International Journal of Production Research. 56 (10), 3699-3713.

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

Wang, X., X. Wang, L. Liang, X. Yue, and L.N. Van Wassenhove. (2017). Estimation of deprivation level functions using a numerical rating scale, Production and Operations Management. 26 (11), 2137-2150.

Wang, Y., and B. Sun. (2018). A Multiobjective Allocation Model for Emergency Resources That Balance Efficiency and Fairness, Mathematical Problems in Engineering. 2018.

Yu, L., C. Zhang, H. Yang, and L. Miao. (2018). Novel methods for resource allocation in humanitarian logistics considering human suffering, Computers & Industrial Engineering. 119, 1-20.

Yu, Y., C. Yu, G. Xu, R.Y. Zhong, and G.Q. Huang. (2020). An operation synchronization model for distribution center in E-commerce logistics service, Advanced Engineering Informatics. 43, 101014.

Yuan, Y., and J. Yu. (2018). Locating transit hubs in a multi-modal transportation network: A cluster-based optimization approach, Transportation Research Part E: Logistics and Transportation Review. 114, 85-103.

Zarbakhshnia, N., Y. Wu, K. Govindan, and H. Soleimani. (2020). A novel hybrid multiple attribute decision-making approach for outsourcing sustainable reverse logistics, Journal of Cleaner Production. 242, 118461.