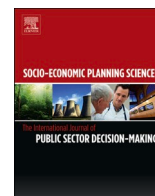




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A stochastic programming model for emergency supplies pre-positioning, transshipment and procurement in a regional healthcare coalition

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ABSTRACT

A regional healthcare coalition enables its member hospitals to conduct an integrated emergency supply management, which is seldom addressed in the existing literature. In this work, we propose a two-stage stochastic emergency supply planning model to facilitate cooperation and coordination in a regional healthcare coalition. Our model integrates pre-disaster emergency supplies pre-positioning and post-disaster emergency supplies transshipment and procurement and considers two planning goals, i.e., minimizing the expected total cost and the maximum supply shortage rate. With some comparison models and a case study on the West China Hospital coalition of Sichuan Province, China, under the background of the COVID-19 epidemic, we demonstrate the effectiveness and benefits of our model and obtain various managerial insights and policy suggestions for practice. We highlight the importance of conducting integrated management of emergency supplies pre-positioning, transshipment and procurement in the regional healthcare coalition for better preparation and responding to future potential disasters.

1. Introduction

Over the past 20 years, disasters of all kinds, such as earthquakes, tsunamis, volcanoes, floods, storms, and epidemics, have occurred with increasing frequency, causing a large number of casualties and substantial economic losses. The International Federation of Red Cross and Red Crescent Societies reports that between 2008 and 2017, natural disasters affected 2 billion people and led to over 1658 US\$ billion economic damage all over the world [1].

After a disaster, lacking and delivering delay of emergency supplies can greatly undermine the emergency response, causing more human suffering. For example, the scarcity of masks, medical protective clothes, and other medical materials created great social panic worldwide and hindered various epidemic control measures at the beginning of the coronavirus disease 2019 (COVID-19) epidemic. As emergency supplies play a key role in treating victims and preventing the spread of the epidemic, effective emergency supplies management is vital for the emergency response to a future epidemic. Field practices indicate that establishing an emergency supply pre-positioning plan helps to ensure that hospitals and other emergency responders can readily obtain emergency supplies for disaster relief. The plan is set before disasters to

pre-stock various emergency supplies (e.g., medicine, food, water, medical equipment) in some strategic emergency warehouses, which are activated after disasters to send out supplies to demand sites and to receive supply replenishment from emergency suppliers. However, the emergency supply planning process is complicated due to uncertain disaster impacts, and it becomes more challenging to consider multiple contradictory emergency management goals. Enhancing the cooperation and coordination among various emergency responders is a key to addressing such challenges. In particular, a healthcare coalition enables various hospitals to collaborate better to improve their emergency supplies management outcomes.

The healthcare coalition is defined as a collaboration among healthcare organizations or entities in a specific region that collaborate in preparing for and responding to public health emergencies in the manner of mutual sharing and aid [2]. Healthcare coalitions help to distribute patients, share scarce medical resources and formulate and implement disaster care standards cooperatively [3], hence are essential for responding to large-scale disasters with a large number of casualties or patients. Specifically, a typical healthcare coalition includes one big (higher-level) central hospital and several small (lower-level) ally hospitals, which are under the guidance of the central hospital. The

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influences of lower-level healthcare organizations on the efficiency of higher-level healthcare organizations in the same region have been recently discussed in the literature [4,5], and there is also recent evidence pointing to the “size matters” factor regarding hospital efficiency [6]. In general, a healthcare coalition has three main functions under emergency: First, rescue information sharing between coalition members and authorities could be promoted, which will lead to consistent situational awareness; Second, it acts as an interface, which helps to improve the efficiency of rescue by accelerating supply sharing and support between coalition members and relevant authorities; Third, it encourages the coordination of member organizations so that the rescue goals, strategy, and tactics are consistent [2].

In a healthcare coalition, coordinated emergency supply support, i.e., delivering emergency supplies between various member hospitals, is possible and vital if emergency demands of a member hospital exceed the pre-stocked emergency supply amounts of that hospital, and the extra demands should be satisfied as soon as possible. Such a practice is common at the beginning of the COVID-19 epidemic. It is reported that the healthcare coalition of West China Hospital (WCH), which is in Sichuan Province of China, employs coordinated emergency supply support to resolve the problem of lacking emergency supplies at some member hospitals. However, the WCH coalition still faces great challenges since it fails to conduct an integrated emergency supply pre-positioning considering uncertain epidemic impacts before the epidemic. Therefore, how to enhance the integrated pre- and post-disaster emergency supply management inside a regional health care coalition is a crucial practical issue. Although various factors, such as uncertain demands, a limited number of emergency vehicles, traffic congestion, perishable supplies, and damaged warehouses, are investigated in the existing emergency supply literature, integrated emergency supply planning for a regional healthcare coalition is understudied.

Inspired by both field practices and the literature, we tackle an integrated emergency supply management problem for a regional healthcare coalition in this study. Our contributions are threefold: 1) We build a two-stage stochastic programming model to conduct integrated planning on the pre-disaster emergency supplies pre-positioning and the post-disaster supplies transshipment and procurement in a regional healthcare coalition; 2) Our solution explicitly considers two planning goals, i.e., cost-effectiveness and emergency service equity; 3) With a case study, we provide managerial insights and policy suggestions for improving the emergency supplies management of healthcare coalitions. The remainder of this article is organized as follows: Section 2 conducts a literature review; Section 3 formally describes our planning problem and presents our model formulation; Section 4 conducts a case study on the WCH coalition in China to obtain managerial insights and policy suggestions; Section 5 concludes our study and proposes future research directions.

2. Literature review

To figure out the research gap, we conduct a literature review from two aspects: the various emergency supply planning models, which are systematically reviewed by Caunhye et al. [7], Özdamar and Ertem [8], Sabbaghtorkan et al. [9], and the research related to healthcare coalitions.

The pre-disaster preparedness and the post-disaster response stages are directly related to the disaster occurrence. In the preparedness stage, emergency supply management issues, like deploying strategic warehouses or facilities and pre-positioning emergency supplies, are widely addressed, and some relevant studies are conducted by Salas et al. [10], Galindo and Batta [11] and Zhang et al. [12]. In the response stage, how to effectively manage the limited emergency supplies attracts a lot of research efforts. Some typical response-stage research issues include emergency inventory control [13,14], emergency service facility location and allocation [15–17], emergency facility location and routing [18], and emergency supply allocation or transportation [19–24]. More

recently, Fragkos et al. [25] deal with post-disaster supply planning for shelters and emergency management crews. Safaei et al. [26] build an integrated bi-level framework for relief logistics operations considering supply risk and demand uncertainty. Yin and Büyüktaktakın [27] propose a multi-stage stochastic epidemic-logistic model, which considers uncertain disease growth and equitable resource allocation.

While the single-stage emergency supply management research can guide the practices in the preparedness stage or the response stage, they suffer from ignoring the inherent connections between the two stages' operations. Therefore, in the recent decade, two-stage emergency supply planning research, which facilitates an integrated and coordinated emergency supply management across stages, has attracted great research efforts. Chang et al. [28] propose two models to determine the relief organizations' structure, locations of emergency warehouses, and distributions of rescue resources for floods. Rawls and Turnquist [29] develop a two-stage stochastic planning model that plans the first-stage emergency warehouse location and emergency supply pre-positioning amounts and the second-stage emergency supply delivering for hurricanes. Mete and Zabinsky [30] deal with the storage and distribution problem of medical supplies to be used under a wide variety of possible disaster types and magnitudes. Duran et al. [14] develop an emergency supply pre-positioning and allocation model that consider impacts of various disasters. Döyen et al. [31] deal with a two-echelon rescue center location and relief allocation problem. Noyan [32] develops a risk-averse two-stage stochastic programming model for the two-stage emergency supply planning problem. Caunhye et al. [33] propose a two-stage location-routing model for emergency supplies pre-positioning and distribution, and they highlight the importance of supplies transshipment. Manopiniwes and Irohara [34] consider facility and stock pre-positioning, evacuation planning and relief vehicle planning in their two-stage stochastic programming model. More recently, Paul and Zhang [35] consider the economic valuation of human suffering, the so-called deprivation cost, in their two-stage emergency supply planning model. Wang and Nie [36] and Hu and Dong [37] propose two-stage stochastic location-allocation models considering non-linear traffic congestion impacts and emergency supplier selections, respectively. Wang and Nie [38] further incorporate network mitigation decisions and consider dynamic factors after disasters. Wang et al. [39] propose a stochastic emergency supply planning model considering lateral supplies transshipment among deployed relief storage facilities after disasters. Sanci and Daskin [40] tackle an integrated location and network restoration problem in disaster relief. We notice that most of the two-stage stochastic programming models for emergency supply management only focus on a cost-effectiveness goal while multiple planning goals (e.g., total operation cost, emergency service equity) should be considered based on practices [7,41,42]. Moreover, we find that the existing two-stage emergency supply planning models do not explicitly consider the cooperation and coordination in a regional healthcare coalition, which plays a vital role in disaster relief.

The existing literature on healthcare coalitions mainly makes qualitative analyses on the roles of healthcare coalitions in emergency relief and the establishment of healthcare coalitions. Courtney et al. [3] maintain that coalition members should develop and follow guidance for supply allocation and alternate care sites deployment to ensure the fairness of supply allocation. Rambhia et al. [43] conduct a survey to reveal the status of the U.S. hospitals joining healthcare coalitions for emergency preparedness and response and to develop guidance for healthcare coalition development and emergency response. Devereaux et al. [44] present a framework for building healthcare coalitions, developing crisis care standards and providing triage team training. To the best of our knowledge, there is a paucity of literature, which conducts quantitative analyses on pre- and post-disaster emergency supply management in regional healthcare coalitions.

In short, the literature review indicates that our work generalizes the existing two-stage emergency supply planning models via integrating the pre-disaster emergency supplies pre-positioning with the post-

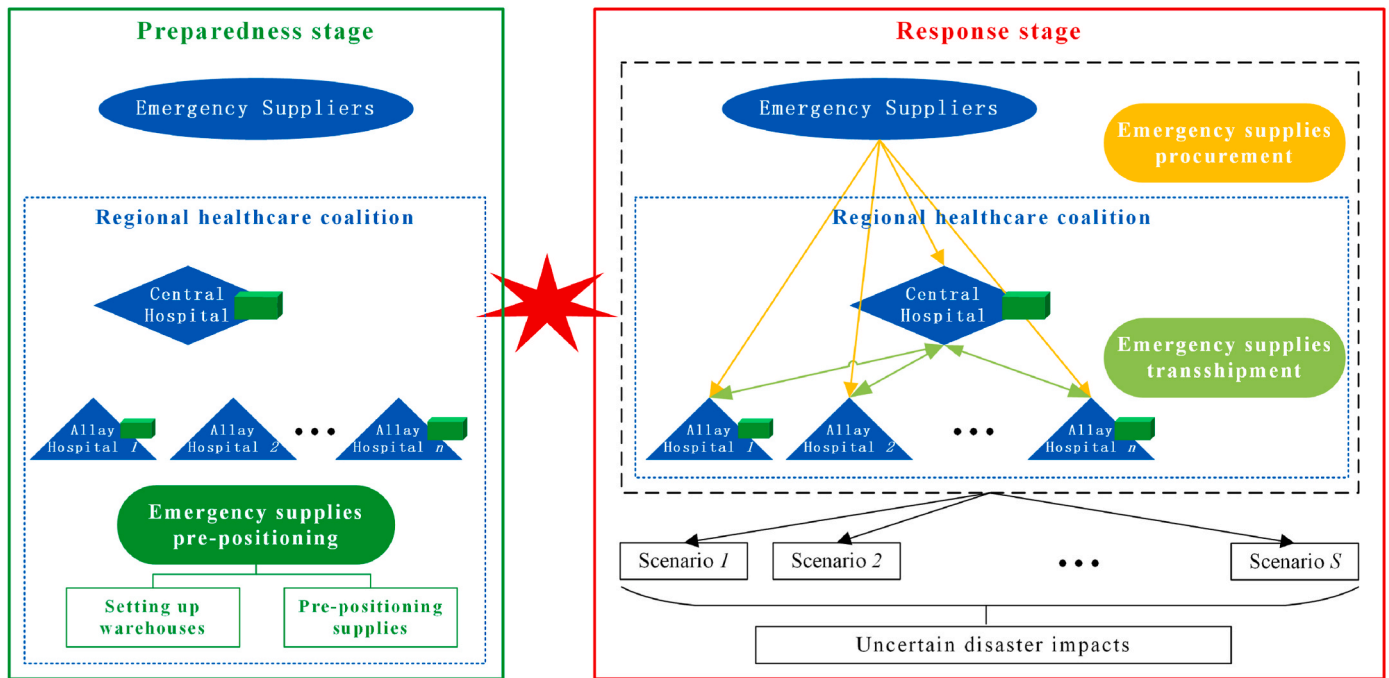


Fig. 1. Problem illustration.

disaster supplies transshipment and procurement, incorporating multiple planning goals and considering the collaboration in a regional healthcare coalition.

3. Problem statement and model formulation

In this section, we first introduce our integrated emergency supply planning problem faced by a regional healthcare coalition. Then, we propose a multi-objective two-stage stochastic programming model to solve this problem and employ a linear weighting method to deal with the two objectives. Finally, we present some comparison models, which are variations of our proposed model.

3.1. Problem statement

A regional healthcare coalition has multiple member hospitals, which normally include a higher-level central hospital (CH) and several lower-level allay hospitals (AHs). In the preparedness stage before disasters, an authority needs to pre-position emergency supplies in the CH and some selected AHs considering uncertain disaster impacts. In the response stage after disasters, the authority needs to plan recourse activities, including emergency supplies transshipments between the CH and AHs and emergency supplies procurements from the member hospitals to emergency suppliers, based on the implemented supplies pre-positioning plan and the realized uncertain disaster impacts. We illustrate this problem in Fig. 1, where the supplies pre-positioning decisions are denoted with various sizes of green cubes. The emergency supplies procurements and transshipments are represented with orange arrows and light-green arrows, respectively, and they are planned for each potential disaster scenario. Since the pre- and post-disaster emergency supplies management decisions are coupled, it is challenging but vital for the authority to conduct an integrated emergency supplies management for the regional healthcare coalition.

We let all member hospitals of the regional healthcare coalition, including the CH and AHs, contain in a set I , and let $\bar{I} \subset I$ include all AHs. Each member hospital $i \in I$ is a candidate emergency warehouse point before disasters and a potential demand point after disasters. Let L be the set of warehouse types. The maximum holding capacity of a type $l \in L$

warehouse is C_l , and the fixed cost of deploying a type l warehouse at member hospital i is denoted as g_{il} . Typically, a central emergency warehouse must be established at the CH before disasters. All emergency supply types form a set K , and we denote the pre-positioning cost and consumed warehouse capacity of unit type $k \in K$ supply as θ_k and c_k , respectively.

Considering uncertain disaster impacts, we let set S contain potential disaster scenarios, and the parameters for each Scenario $s \in S$ are superscripted with an s . We denote the occurrence probability of each Scenario s as P^s , and let the post-disaster demand of type k emergency supply in member hospital i be d_{ki}^s . To supplement the pre-positioned emergency supplies, all member hospitals can urgently purchase emergency supplies from some suppliers (or producers), which are contained in a set J . We denote the emergency procurement cost for member hospital i to buy unit type k supply from supplier $j \in J$ as p_{kij}^s . Considering that the CH and AHs have different bargain power against the suppliers due to their different levels and sizes, it normally costs the lower-level AHs more than the higher-level CH to buy unit type k supply from supplier j after disasters. Since a disaster can also undermine the supply (production) capacity of the suppliers, we denote the maximum amount of type k supply that can be provided by supplier j as m_{kj}^s . We let the unit shortage cost (due to unmet demands) and the unit holding cost (due to over-stocking) of type k supply in member hospital i be ν_{ki}^s and μ_{ki}^s , respectively. We assume that the mutual aids between the CH and each AH $i' \in \bar{I}$ take a unit supply delivering cost of $t_{i'}^s$, and that the unit supply delivering cost from emergency supplier j to member hospital i is τ_{ji}^s . We assume that $t_{i'}^s$ and τ_{ji}^s are most closely related to the time value associated with the various emergency supply delivering time. Thus, we keep $\tau_{ji}^s > t_{i'}^s, \forall i' \in \bar{I}, s \in S$, which indicate that the mutual aids between CH and AHs inside the healthcare coalition are much faster than the emergency procurement from suppliers. Moreover, we assume that the emergency supply orders from AH i' to the CH, from CH to AH i' , and from member hospital i to emergency supplier j take fixed costs of $o_{i'}$, $q_{i'}$, and f_{ij} , respectively.

In the first-stage before disasters, the authority needs to deploy emergency warehouses and pre-position emergency supplies in the healthcare coalition. Specifically, we apply binary decision variables z_{il}

Table 1

Notations.

Sets
I , all member hospitals in a regional healthcare coalition, including a CH and multiple AHs, $i \in I$
\bar{I} , all AHs in the regional healthcare coalition, $i' \in \bar{I}, \bar{I} \subset I$
J , emergency suppliers, $j \in J$
K , emergency supply types, $k \in K$
L , warehouse types, $l \in L$
S , disaster scenarios, $s \in S$
Parameters
C_l , maximum holding capacity of a type l warehouse
c_k , holding capacity consumed by unit type k supply
g_{il} , fixed cost of setting up a type l warehouse at a member hospital i
o_i , fixed cost of an request from AH i' to CH
q_i , fixed cost of an request from CH to AH i'
f_{ij} , fixed cost of an order from a member hospital i to an emergency supplier j
θ_k , pre-positioning cost of unit type k supply
P^s , occurrence probability of disaster scenario s
$t_{i'}^s$, unit supply delivering cost between CH and AH i' under scenario s
t_{ij}^s , unit supply delivering cost from supplier j to member hospital i under scenario s
v_{ki}^s , shortage cost of unit type k supply in member hospital i under scenario s
μ_{ki}^s , holding cost of unit type k supply in member hospital i under scenario s
d_{ki}^s , demand of type k supply in member hospital i under scenario s
m_{kj}^s , maximum amount of type k supply available at supplier j under scenario s
p_{kij}^s , emergency procurement cost for member hospital i to buy unit type k supply from supplier j under scenario s
ω , a relative weighting coefficient for our second planning goal
M , a huge positive number
Decision variables
$z_{il} \in \{0, 1\}$, 1, if a type l warehouse is set up at a member hospital i ; 0, otherwise
$x_{ki} \geq 0$, amount of type k supply pre-positioned in member hospital i
$y_{ij}^s \in \{0, 1\}$, 1, if member hospital i places an order to buy supply from supplier j under scenario s ; 0, otherwise
$a_i^s \in \{0, 1\}$, 1, if CH requests supply support from AH i' under scenario s ; 0, otherwise
$b_i^s \in \{0, 1\}$, 1, if AH i' requests supply support from CH under scenario s ; 0, otherwise
$r_{kji}^s \geq 0$, amount of type k supply shipped from supplier j to member hospital i under scenario s
$w_{ki}^s \geq 0$, amount of type k supply shipped from CH to AH i' under scenario s
$v_{ki}^s \geq 0$, amount of type k supply shipped from AH i' to CH under scenario s
$u_{ki}^s \geq 0$, unmet demand amount of type k supply at member hospital i under scenario s
$h_{ki}^s \geq 0$, holding amount of type k supply at member hospital i under scenario s

$\in \{0, 1\}$ to decide if a type l warehouse is deployed at a member hospital i , and employ $x_{ki} \geq 0$ to determine the amount of pre-positioned type k supply in member hospital i . In the second-stage after disasters, the authority needs to decide the emergency supply procurement and transshipment according to the pre-disaster emergency supply pre-positioning and the realized uncertain disaster impacts. For each disaster scenario s , we apply binary variables $y_{ij}^s \in \{0, 1\}$, $a_i^s \in \{0, 1\}$, and $b_i^s \in \{0, 1\}$ to decide if member hospital i places an order to purchase emergency supply from supplier j , if CH requests emergency supply support from AH i' , and if AH i' requests emergency supply support from CH, respectively. We use continuous variables $r_{kji}^s \geq 0$, $w_{ki}^s \geq 0$ and $v_{ki}^s \geq 0$ to denote the amounts of type k supply shipped from supplier j to member hospital i , from CH to AH i' , and from AH i' to CH, respectively. Moreover, we employ $u_{ki}^s \geq 0$ and $h_{ki}^s \geq 0$ to determine the unmet demand amount and the holding amount of type k supply at member hospital i , respectively. We summarize all notations in Table 1.

3.2. Model formulation

The integrated emergency supply planning problem faced by a regional healthcare coalition can be formulated as the following multi-objective two-stage stochastic programming model (MP):

$$\begin{aligned}
 \text{(MP)} \quad \min \quad & \sum_{i \in I} \sum_{l \in L} g_{il} z_{il} + \sum_{i \in I} \sum_{k \in K} \theta_k x_{ki} + \\
 & \sum_{s \in S} P^s \sum_{i' \in \bar{I}} \left(q_{i'} a_{i'}^s + o_{i'} b_{i'}^s + \sum_{k \in K} t_{i'}^s (w_{ki}^s + v_{ki}^s) \right) + \\
 & \sum_{s \in S} P^s \sum_{i \in I} \sum_{j \in J} \left(f_{ij} y_{ij}^s + \sum_{k \in K} (p_{kij}^s + \tau_{ji}^s) r_{kji}^s \right) + \\
 & \sum_{s \in S} P^s \sum_{i \in I} \sum_{k \in K} (v_{ki}^s u_{ki}^s + \mu_{ki}^s h_{ki}^s),
 \end{aligned} \tag{1}$$

$$\min \quad \max_{i \in I, k \in K} \sum_{s \in S} P^s \left(\frac{u_{ki}^s}{d_{ki}^s} \right), \tag{2}$$

$$\text{s.t.} \quad \sum_{l \in L} z_{il} = 1, \quad \forall i \in I : i \notin \bar{I}, \tag{3}$$

$$\sum_{l \in L} z_{il} \leq 1, \quad \forall i \in \bar{I}, \tag{4}$$

$$\sum_{k \in K} x_{ki} C_k \leq \sum_{l \in L} z_{il} C_l, \quad \forall i \in I, \tag{5}$$

$$\sum_{k \in K} v_{ki}^s \leq a_i^s M, \quad \forall i \in \bar{I}, s \in S, \tag{6}$$

$$v_{ki}^s \leq x_{ki}, \quad \forall i \in \bar{I}, k \in K, s \in S, \tag{7}$$

$$\sum_{k \in K} w_{ki}^s \leq b_i^s M, \quad \forall i \in \bar{I}, s \in S, \tag{8}$$

$$\sum_{i' \in \bar{I}} w_{ki}^s \leq x_{ki}, \quad \forall i \in I : i \notin \bar{I}, k \in K, s \in S, \tag{9}$$

$$\sum_{k \in K} r_{kji}^s \leq y_{ij}^s M, \quad \forall i \in I, j \in J, s \in S, \tag{10}$$

$$\sum_{i \in I} r_{kji}^s \leq m_{kj}^s, \quad \forall k \in K, j \in J, s \in S, \tag{11}$$

$$x_{ki} + \sum_{j \in J} r_{kji}^s + \sum_{i' \in \bar{I}} v_{ki}^s = \sum_{i' \in \bar{I}} w_{ki}^s + h_{ki}^s + d_{ki}^s - u_{ki}^s, \quad \forall i \in I : i \notin \bar{I}, k \in K, s \in S, \tag{12}$$

$$x_{ki'} + \sum_{j \in J} r_{kji}^s + w_{ki'}^s = v_{ki'}^s + h_{ki'}^s + d_{ki'}^s - u_{ki'}^s, \quad \forall i' \in \bar{I}, k \in K, s \in S, \tag{13}$$

$$z_{il} \in \{0, 1\}, \quad \forall i \in I, l \in L, \tag{14}$$

$$x_{ki} \geq 0, \quad \forall k \in K, i \in I, \tag{15}$$

$$y_{ij}^s \in \{0, 1\}, \quad \forall i \in I, j \in J, s \in S, \tag{16}$$

$$a_i^s \in \{0, 1\}, \quad \forall i \in \bar{I}, s \in S, \tag{17}$$

$$b_i^s \in \{0, 1\}, \quad \forall i \in \bar{I}, s \in S, \tag{18}$$

$$w_{ki'}^s \geq 0, \quad \forall k \in K, i' \in \bar{I}, s \in S, \tag{19}$$

$$v_{ki'}^s \geq 0, \quad \forall k \in K, i' \in \bar{I}, s \in S, \tag{20}$$

$$r_{kji}^s \geq 0, \quad \forall k \in K, i \in I, j \in J, s \in S, \tag{21}$$

$$u_{ki}^s \geq 0, \quad \forall k \in K, i \in I, s \in S, \tag{22}$$

$$h_{ki}^s \geq 0, \quad \forall k \in K, i \in I, s \in S. \tag{23}$$

Model (MP) considers two planning goals, i.e., cost-effectiveness and service equity, with objective functions (1) and (2), respectively. Objective (1) minimizes the expected total cost, which includes the pre-disaster emergency preparedness cost and the expected post-disaster emergency response cost. The preparedness cost contains the warehouse deployment cost ($g_{il}z_{il}$) and the supply pre-positioning cost ($\theta_k x_{ki}$). The expected emergency response cost includes costs related to the emergency transshipments between CH and AHs, i.e., $q_i a_i^s + o_i b_i^s + \sum_{k \in K} t_i^s (w_{ki}^s + v_{ki}^s)$, costs related to the emergency procurement from member hospitals to suppliers, i.e., $f_{ij} y_{ij}^s + \sum_{k \in K} (p_{kij}^s + \tau_{ji}^s) r_{kji}^s$, the unmet demand penalty cost ($\nu_{ki}^s u_{ki}^s$) and the inventory holding cost ($\mu_{ki}^s h_{ki}^s$). Specifically, the emergency transshipment relevant costs include the emergency request cost ($q_i a_i^s + o_i b_i^s$) and the supply delivering cost ($t_i^s w_{ki}^s + t_i^s v_{ki}^s$), and the emergency procurement relevant costs include the ordering cost ($f_{ij} y_{ij}^s$), the purchasing cost ($p_{kij}^s r_{kji}^s$) and the supply delivering cost ($\tau_{ji}^s r_{kji}^s$). Objective (2) helps to improve the emergency service equity via minimizing the maximum expected supply shortage rate over all member hospitals and supply types. The min-max objective function (2) can be linearized with the following objective function (24) and auxiliary constraints (25) and (26):

$$\min \quad SR, \tag{24}$$

$$SR \geq \sum_{s \in S} P^s \left(\frac{u_{ki}^s}{a_{ki}^s} \right), \quad \forall i \in I, k \in K, \tag{25}$$

$$SR \geq 0. \tag{26}$$

Constraints (3)–(5) are related to the first-stage emergency supply pre-positioning decisions. Constraints (3) ensure that the CH establishes a central emergency warehouse, and Constraints (4) indicate that each AH can deploy at most one emergency warehouse of any type. However, if the CH does not have to establish a central warehouse in field practices, our (MP) can become more general by simply replacing Constraints (3) and (4) with $\sum_{l \in L} z_{il} \leq 1, \forall i \in I$. Constraints (5) ensure that the capacity consumed by all pre-positioned supplies cannot exceed the maximum holding capacity of the deployed warehouse.

Constraints (6)–(13) are for the second-stage emergency supply procurement and transshipment under each disaster scenario $s \in S$. Constraints (6)–(9) are related to the supply transshipment between the CH and AHs. Constraints (6) and (7) ensure that supplies can be shipped from an AH to the CH once CH makes the request and that the delivering amount should be less than the pre-positioned supply amount at that AH. Similarly, Constraints (8) and (9) are for supply support from the CH to each AH. Constraints (10) and (11) are related to the emergency supply procurement from each member hospital to each supplier. Constraints (10) ensure that emergency supplies can be delivered from supplier j to member hospital i only after corresponding orders are made. Constraints (11) limit the supply capacity of each supplier. Constraints (12) and (13) ensure that the emergency supply flows are balanced at the CH and AHs, respectively. The other constraints (14)–(23) set bounds for the binary variables and the non-negative continuous variables.

We employ the linear-weighting method to deal with our two plan-

ning goals and to modify our (MP) as the following single-objective programming model (P):

$$(P) \quad \min \quad TC + \omega SR, \tag{27}$$

$$\begin{aligned} \text{s.t.} \quad & TC = \sum_{i \in I} \sum_{l \in L} g_{il} z_{il} + \sum_{i \in I} \sum_{k \in K} \theta_k x_{ki} + \\ & \sum_{s \in S} P^s \sum_{i \in \bar{I}} \left(q_i a_i^s + o_i b_i^s + \sum_{k \in K} t_i^s (w_{ki}^s + v_{ki}^s) \right) + \\ & \sum_{s \in S} P^s \sum_{i \in I} \sum_{j \in J} \left(f_{ij} y_{ij}^s + \sum_{k \in K} (p_{kij}^s + \tau_{ji}^s) r_{kji}^s \right) + \\ & \sum_{s \in S} P^s \sum_{i \in I} \sum_{k \in K} (\nu_{ki}^s u_{ki}^s + \mu_{ki}^s h_{ki}^s), \end{aligned} \tag{28}$$

$$TC \geq 0, \tag{29}$$

Constraints (3) – (23) and (25) – (26),

where ω is a relative weighting coefficient for our second planning goal. In field practices, the decision-maker can set the weighting coefficient ω according to the relative importance of the second goal in the emergency supplies management of the regional healthcare coalition. Although other approaches (e.g., ϵ -constraint method, lexicographic method) can be applied to handle our multi-objective optimization, we employ the linear weighting method mainly for its simplicity, which is vital for field applications.

3.3. Comparison models

To show the benefits of our proposed model (P) and to obtain managerial insights, we consider four comparison models, i.e., (CP1) to (CP4), which are variations of (P) and implement other emergency supply management strategies for the regional healthcare coalition. The settings of the comparison models are discussed below.

(CP1): Only the CH has an emergency warehouse, and the emergency demands of AHs can be satisfied by supplies shipped from both the CH and the suppliers. (CP1) is set by replacing Constraints (4) with $\sum_{l \in L} z_{il} = 0, \forall i \in \bar{I}$.

(CP2): The CH does not establish a central warehouse while AHs can deploy emergency warehouses, and emergency supplies can be delivered from AHs to the CH. (CP2) is set via modifying Constraints (3) as $\sum_{l \in L} z_{il} = 0, \forall i \in I : i \notin \bar{I}$.

(CP3): The CH has an emergency warehouse, and AHs can deploy their own emergency warehouses, but there is no coordinated emergency supply support between CH and AHs. (CP3) is set via adding extra constraints $v_{ki}^s = 0, \forall i \in \bar{I}, k \in K, s \in S$ and $w_{ki}^s = 0, \forall i \in \bar{I}, k \in K, s \in S$ to (P).

(CP4): No member hospitals establish emergency warehouses, which indicates that there is no emergency supply pre-positioning or transshipment in the regional healthcare coalition. (CP4) is set via replacing Constraints (3) and (4) with $\sum_{l \in L} z_{il} = 0, \forall i \in I : i \notin \bar{I}$ and $\sum_{l \in L} z_{il} = 0, \forall i \in \bar{I}$, respectively.

The settings of (P) and the four comparison models are summarized in Table 2.

Table 2
Settings of various models.

Model	Supplies pre-positioning		Supplies transshipment
	CH	AHs	
(P)	✓	✓	✓
(CP1)	✓	×	✓
(CP2)	×	✓	✓
(CP3)	✓	✓	×
(CP4)	×	×	×

4. Case study

In this section, we present a case study on the WCH coalition of Sichuan Province, China, under the background of the COVID-19 epidemic. We first introduce the basic parameter settings of this case. Then, we compare the optimal solutions of various models. Finally, we conduct sensitivity analyses on some key parameters to obtain managerial insights and policy suggestions.

4.1. Parameters settings

The WCH coalition covers a population of 33.79 millions over 216,100 square kilometres of Sichuan province, China, and plays a vital role during the COVID-19 epidemic. The locations of WCH and its 11 key AHs (i.e., AH1-AH11) are illustrated in Fig. 2.

WCH, founded in 1872 and located in Chengdu (capital city of Sichuan Province, China), has been the largest hospital in China and ranks the first for its science & technology influence. WCH has 206 ICU beds and over 4300 total beds, and it functions well to fight against COVID-19 [45]. During the COVID-19 epidemic, WCH offered emergency supplies to its AHs and provided emergency support to other cities in China. The 11 key AHs of WCH are also leading hospitals in other cities of Sichuan Province. Without loss of generality, we focus on the central hospital, WCH, and its two largest and representative ally hospitals, AH1 (near to WCH) and AH2 (far from WCH), which also have the most emergency demands during the COVID-19 epidemic. WCH and the two AHs are marked in red in Fig. 2. For simplicity, we consider two emergency suppliers (ES1 and ES2) of the WCH coalition, two emergency supply types, i.e., medical mask (MM) and protective clothes (PC), and two warehouse types (Small and Big).

According to field practices, the holding capacities C_l of the Small and Big warehouses are set as 800 boxes and 1500 boxes, respectively. The warehouse holding capacities consumed by each unit of pre-positioned MM and PC (c_k) are 1 box and 3 boxes, respectively, and the unit pre-positioning costs of MM and PC (θ_k) are \$5 and \$25, respectively. We assume that the fixed emergency request costs o_f from AH1 and AH2 to WCH are \$200 and \$250, respectively, and the request costs q_f from WCH to the two AHs are \$300. Settings of the other parameters, which are unrelated to the epidemic scenarios, are listed in Table 3. For simplicity, we assume that the delivering costs of emergency

Table 3

Settings of parameters related to each member hospital.

Hospital	g_{il} (\$)		f_{ij} (\$)		τ_{ji}^s (\$/box)		t_i^s (\$/box)
	Small	Big	ES1	ES2	ES1	ES2	
WCH	18,000	27,000	200	300	10	5	-
AH1	18,000	27,000	250	350	15	10	3
AH2	18,000	27,000	350	450	20	15	6

procurement (τ_{ji}^s) and emergency transshipment (t_i^s) are the same in each scenario, and set their values according to the travel distances from the suppliers to the three member hospitals as well as the distances from WCH to the two AHs.

We consider three epidemic scenarios, mild scenario $s1$, medium scenario $s2$ and severe scenario $s3$, which have occurrence probabilities of 0.1, 0.3 and 0.6, respectively. The scenario-based parameters, including the emergency demands d_{ki}^s , the unit supply shortage costs ν_{ki}^s , the unit supply holding costs μ_{ki}^s , the total available inventory amounts of suppliers m_{kj}^s and the unit supply procurement costs p_{kij}^s , are listed in Tables 4 and 5. In general, the settings of the scenario-based parameters are based on real data and educated guessing. The demands of the three member hospitals are estimated from the emergency supply demand data during the COVID-19 epidemic. The shortage cost and the holding cost are arbitrarily assumed considering the various sizes and levels of the member hospitals and the relevant negative social impacts. The unit supply procurement costs p_{kij}^s and the total available inventory amounts of suppliers m_{kj}^s are adapted from real data of all member hospitals and emergency suppliers. Overall, Tables 4 and 5 indicate that as the severity of the epidemic scenario increase, the values of d_{ki}^s , ν_{ki}^s and p_{kij}^s gradually increase while the values of μ_{ki}^s and m_{kj}^s gradually decrease. Finally, we arbitrarily let the weighting coefficient ω be 1, 000 in the base case setting.

4.2. Optimal results

We apply Gurobi to solve (P) and (CP)s optimally, and all solving processes run on an ordinary laptop, which is equipped with an Intel Core i5-7200U @2.50 GHz CPU, 12 GB RAM, and Microsoft Windows 10 operating system. The solution time is less than a second. The optimal

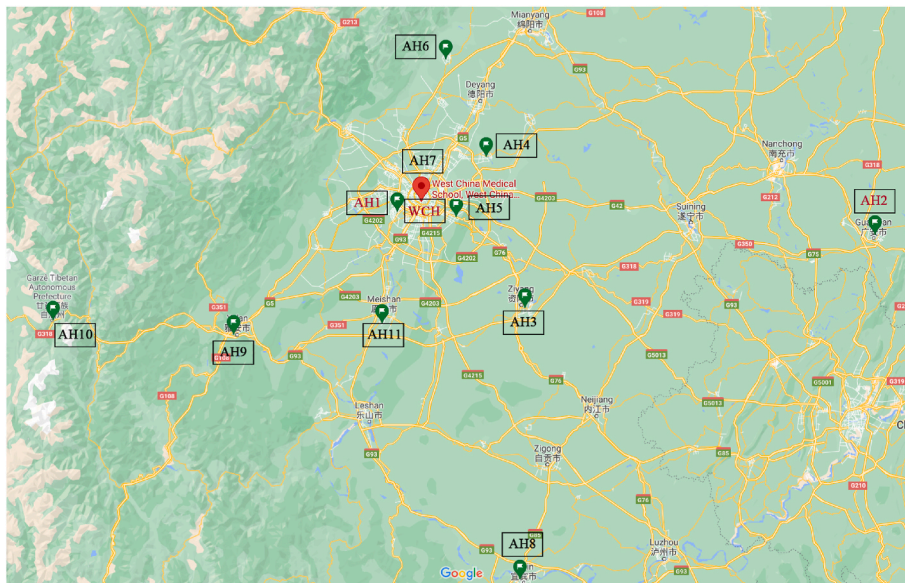


Fig. 2. Locations of WCH and its 11 key AHs.

Table 4
Settings of d_{ki}^s , ν_{ki}^s , μ_{ki}^s and m_{kj}^s

Scenario	Type	d_{ki}^s (box)			ν_{ki}^s (\$/box)			μ_{ki}^s (\$/box)			m_{kj}^s (box)	
		WCH	AH1	AH2	WCH	AH1	AH2	WCH	AH1	AH2	ES1	ES2
s1	MM	750	555	450	15	15	15	2	3	3	1500	1000
	PC	300	180	240	60	60	60	4	5	5	400	300
s2	MM	900	675	600	20	20	20	2	2	2	1000	750
	PC	450	270	300	70	70	70	3	4	3	300	250
s3	MM	1425	1050	900	30	30	30	1	1	1	750	500
	PC	525	375	420	90	90	90	1	1	1	200	150

Table 5
Settings of p_{kij}^s (\$/box).

Scenario	Hospital	MM		PC	
		ES1	ES2	ES1	ES2
s1	WCH	6	7	30	33
	AH1	7	8	35	38
	AH2	7	8	35	38
s2	WCH	8	10	45	50
	AH1	10	12	50	60
	AH2	10	12	50	60
s3	WCH	12	15	60	66
	AH1	14	16	70	74
	AH2	14	16	70	74

solution values of various models are compared in Table 6.

The comparison between (P) and (CP1) highlights the importance of allowing AHs to pre-position emergency supplies. Although the weighted total cost of (CP1) is only about 1.3% more than that of (P), the expected SR and penalty cost of (CP1) are about 55% and 103% more than those of (P), respectively. This indicates that if AHs can pre-position emergency supplies, the expected SR and penalty cost can be greatly reduced to enhance the emergency response performance of the healthcare coalition as a whole. The comparison between (P) and (CP2) shows that setting up an emergency warehouse at the CH may not always be part of the optimal solution for the regional healthcare coalition. In particular, we find that the weighted total cost of (CP2) is about 1.5% less than that of (P) owing to the lower expected transshipment cost, penalty cost, and SR of (CP2). (CP3) assumes no coordinated emergency supplies transshipment in the healthcare coalition. The comparison between (P) and (CP3) shows that the weighted total cost and SR of (CP3) are about 1% more and 24% less than that of (P), respectively. This implies that although ignoring emergency supplies transshipment increases the expected TC (mostly due to the raised setup and pre-positioning costs), it can reduce the expected penalty cost and SR and improve the emergency service equity of the healthcare coalition. However, the comparison between (P) and (CP3) emphasizes that coordinated emergency supplies transshipment between CH and AHs is vital for improving the emergency plan's weighted total cost. In (CP4), no member hospitals pre-position emergency supplies, and all emergency demands are satisfied via emergency procurement from suppliers. Although the weighted total cost of (CP4) is lower than those of (CP1) and (CP3), (CP4) has the highest expected procurement cost, penalty

cost, and SR in Table 6. In particular, the expected TC, SR, and weighted total cost of (CP4) are about 0.7%, 55%, and 1.1% higher than those of (P), respectively. This highlights the importance of pre-positioning emergency supplies in the healthcare coalition before disasters.

We illustrate the optimal emergency supplies pre-positioning and delivering plans of (P) and (CP)s in Figs. 3–7 to gain managerial insights. In general, we find that only big warehouses (denoted with green cubes) are established in Figs. 3–6 and that as the epidemic severity increases from Scenario s1 to Scenario s3, the amounts of transshipped emergency supplies gradually reduce, and WCH procure increasingly more emergency supplies from the suppliers. This indicates that 1) the emergency supplies transshipment is more vital for effectively responding to mild or medium epidemic scenarios, and 2) WCH, due to its relatively higher bargain power and emergency supply demands, is prioritized to procure the limited emergency supplies first under all scenarios.

Moreover, Figs. 3 and 4 highlight the importance of pre-positioning emergency supplies at AH2, which is far from WCH and AH1. Under Scenarios s2 and s3, while the emergency demands of AH2 are partially served by the pre-positioned supplies in Fig. 3, they are not served at all in Fig. 4, which contributes to the high SR of (CP1) in Table 6. Fig. 5 shows that if emergency supplies are not pre-positioned at WCH, the demands of WCH are served by the emergency procurement (transshipment) from the suppliers (AHs), while the demands of AHs are mainly satisfied by their pre-positioned supplies. To effectively support WCH and reduce emergency procurement in the response stage, AH1 and AH2 deploy big emergency warehouses to pre-stock more supplies. This observation suggests an alternative solution to a regional healthcare coalition, which does not require the CH to pre-stock emergency supplies. Fig. 6 shows that the absence of emergency supplies transshipment leads each member hospital to deploy a big warehouse and to pre-stock emergency supplies for its own use, which explains the high setup and pre-positions costs of (CP3) in Table 6. This observation implies that the emergency supplies transshipment can make the emergency supplies pre-positioning more economical for the whole coalition and help avoid waste of pre-stocked supplies, which have limited shelf life. Thus, a government should develop policies for enhancing the cooperation and coordination of emergency supplies management in the regional healthcare coalition. Finally, Fig. 7 shows that the absence of emergency supplies pre-positioning requires member hospitals to procure more supplies from suppliers under emergency urgently, and it becomes increasingly harder for the AHs to procure emergency supplies as the severity of the epidemic increase. Thus, without emergency supplies pre-positioning, it is more vital for AHs to sign up emergency

Table 6
Optimal solution values of various models.

Model	Cost components (\$)						TC (\$)	SR	Weighted Total (\$)
	Setup	Pre-position	Transship	Procure	Holding	Penalty			
(P)	54,000	20,700	2403.5	43,098	0	37,440	157,642	44.8%	158,090
(CP1)	27,000	9900	2356	44,035	0	75,892.5	159,184	99.3%	160,177
(CP2)	54,000	20,250	505.5	44,059.5	0	36,630	155,445	24%	155,685
(CP3)	81,000	30,700	0	34,528	169.5	13,500	159,898	20%	160,098
(CP4)	0	0	0	49,015	0	109,778	158,792	100%	159,792

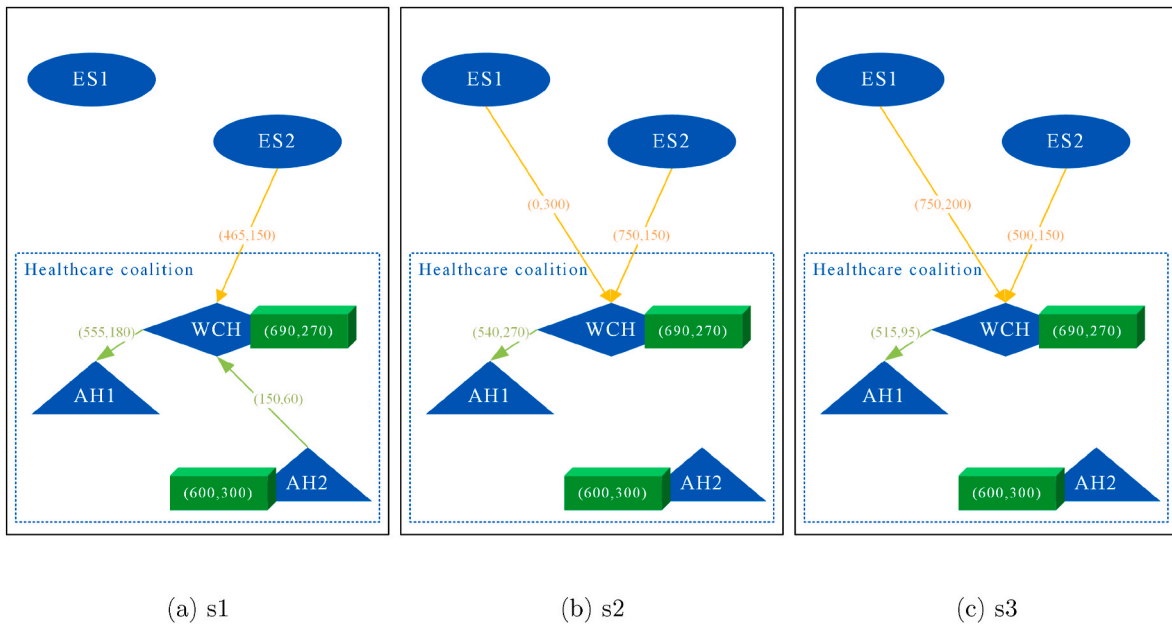


Fig. 3. Emergency supplies pre-positioning and delivering plan of (P).

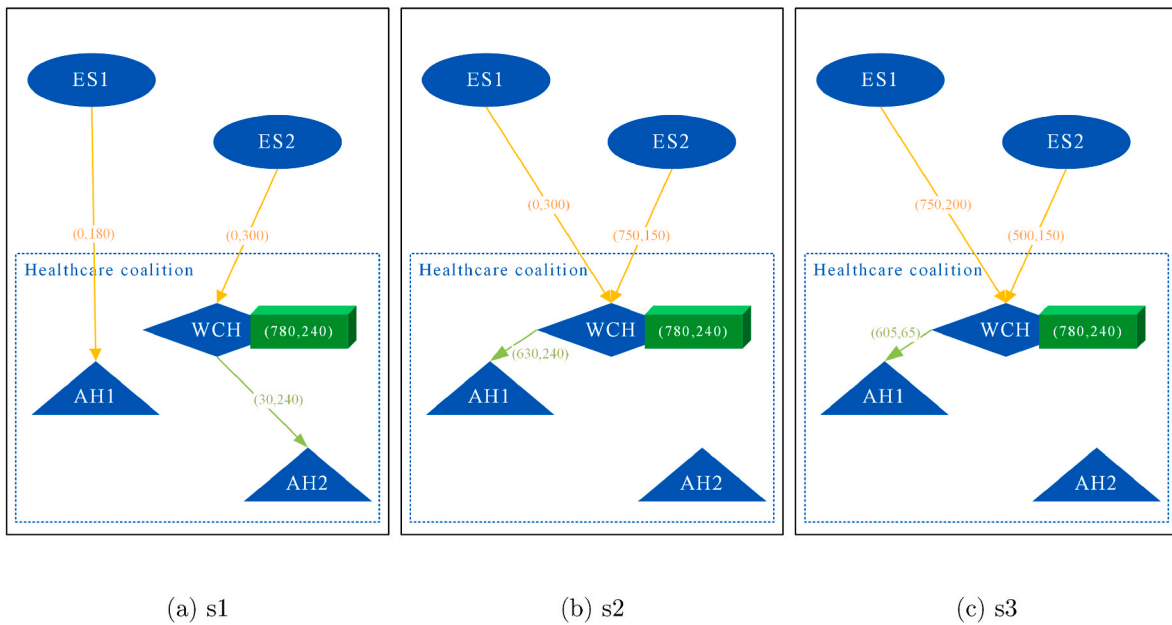


Fig. 4. Emergency supplies pre-positioning and delivering plan of (CP1).

procurement contracts with suppliers to ensure that certain amounts of emergency supplies can be urgently procured even under the more severe epidemic scenarios.

4.3. Sensitivity analyses

We conduct sensitivity analyses on three parameters, i.e., the weighting coefficients of the service equity goal ω , the unit supply delivering cost τ_{ji}^s , and the unit supply shortage cost ν_{ki}^s , which can be

hard to estimate in practice and can help us to gain more managerial insights.

In our base case, ω is 1000. We examine impacts of ω via modifying the value of ω from 500 to 1500 with a step size of 100. The optimal results for various values of ω are illustrated in Fig. 8.

In Subfigure 8(a), as ω increases, the weighted total cost gradually increases with a decreasing speed. In Subfigure 8(b), the trade-off between TC and SR is obvious. In particular, with ω increasing, TC gradually rises while SR decreases from 59% down to a limit, about 24%. The

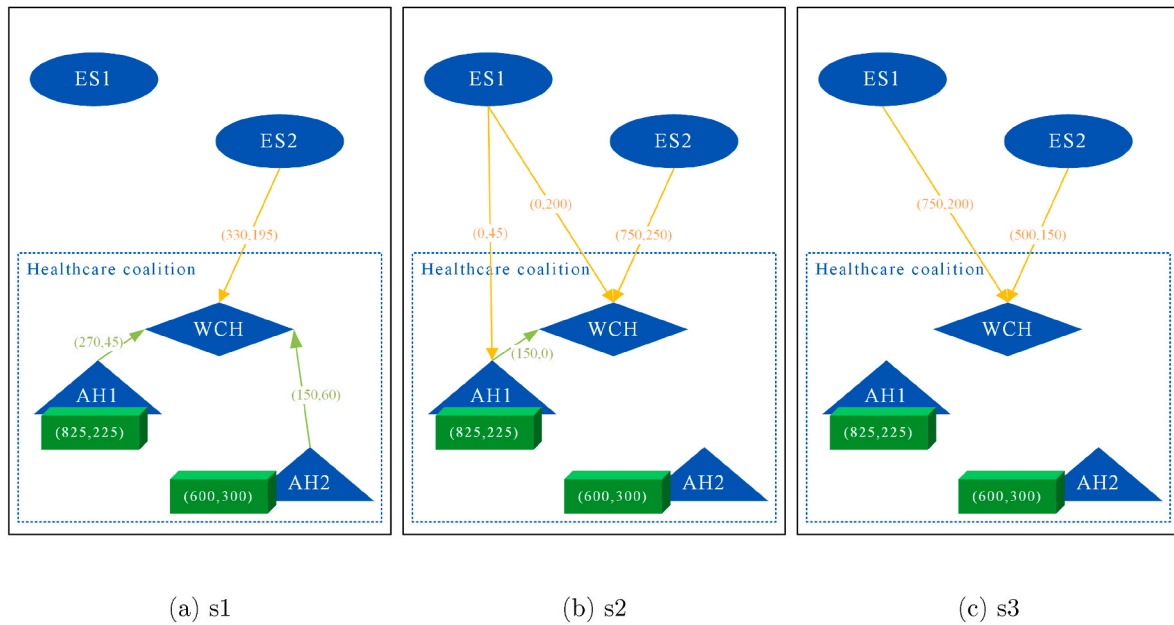


Fig. 5. Emergency supplies pre-positioning and delivering plan of (CP2).

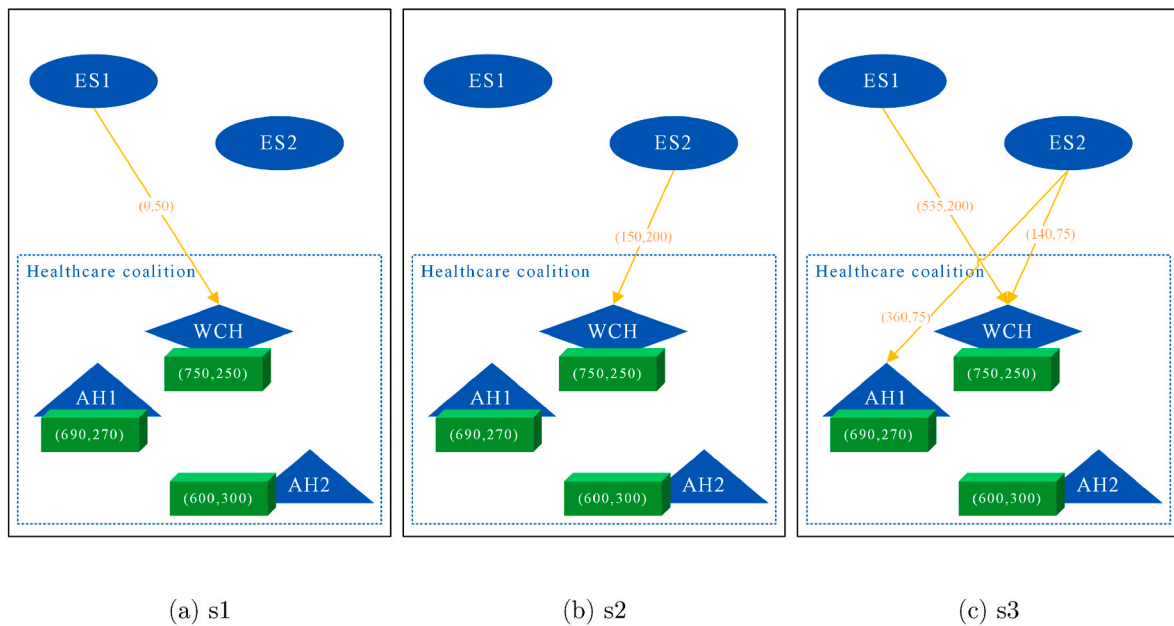


Fig. 6. Emergency supplies pre-positioning and delivering plan of (CP3).

lower bound for SR can be due to the maximum pre-positioning (emergency supply) capacity of the healthcare coalition (suppliers). Thus, to obtain more equity (e.g., let SR be 0%) in the coalition, purely increasing ω can be insufficient, and the authority may also need to improve the maximum pre-positioning (emergency supply) capacity of the coalition (suppliers) with supportive activities and motivation policies. Moreover, Subfigures 8(c) and 8(d) show the impacts of ω on the various cost components of TC. We find that when $\omega \leq 800$ or $\omega \geq 1,300$

($800 \leq \omega \leq 1300$), the optimal plans pre-stock less (more) emergency supplies and conduct more (less) emergency supply procurement and transshipment after the epidemic. This shows that the relative importance of the service equity goal can influence the trade-off between the pre- and post-epidemic emergency supplies management measures, e.g., when more (less) supplies are pre-positioned, less (more) emergency supplies transshipment and procurement are needed. In short, Fig. 8 highlights that ω should be properly set to achieve a desired trade-off

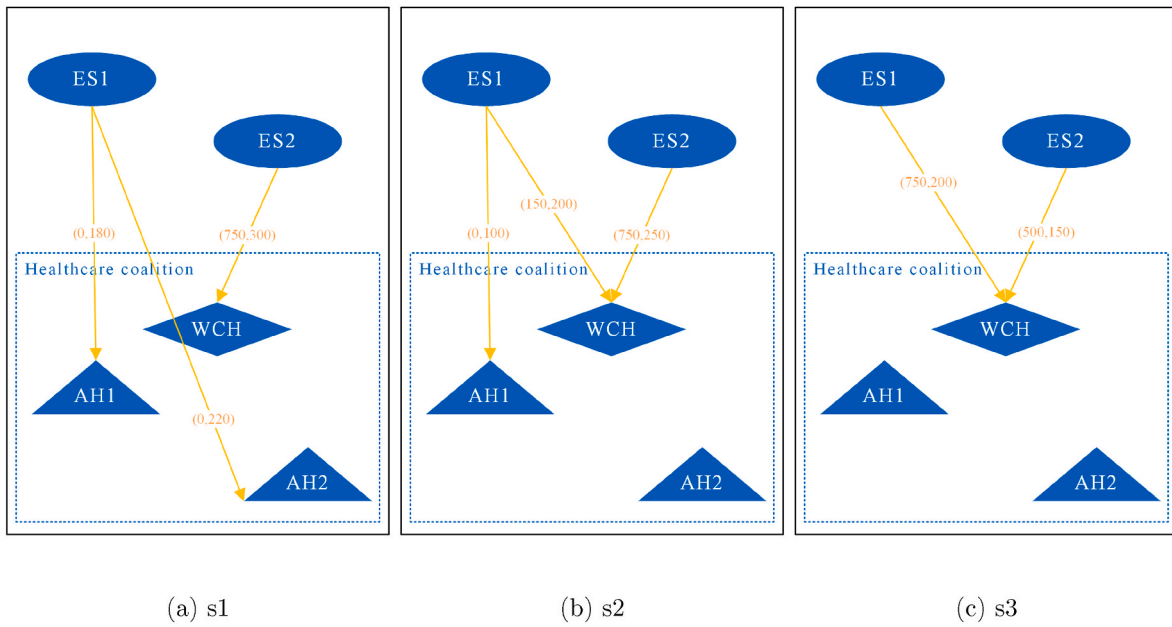
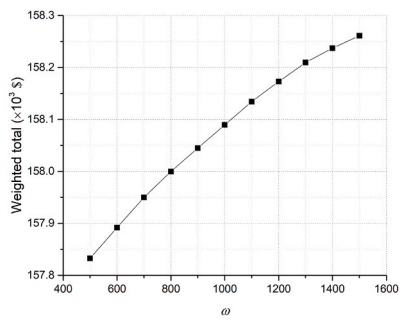
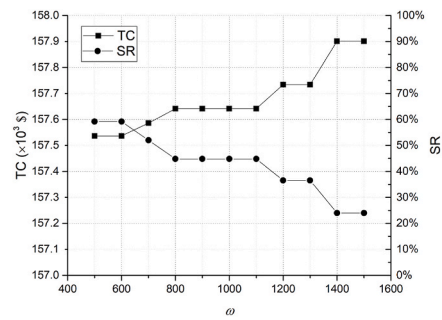


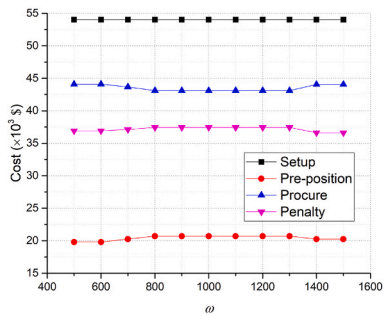
Fig. 7. Emergency supplies pre-positioning and delivering plan of (CP4).



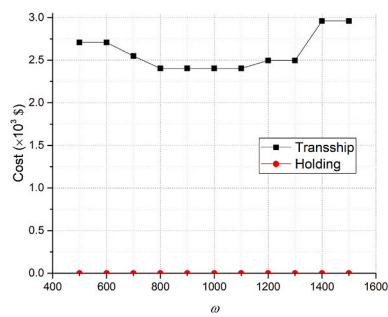
(a) Impacts on the weighted total costs



(b) Impacts on TC and SR

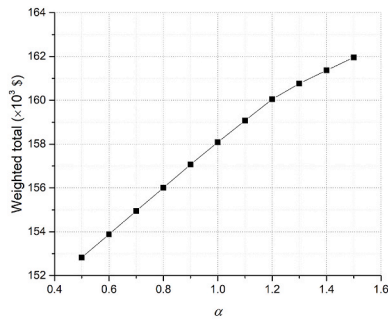


(c) Impacts on the various cost components

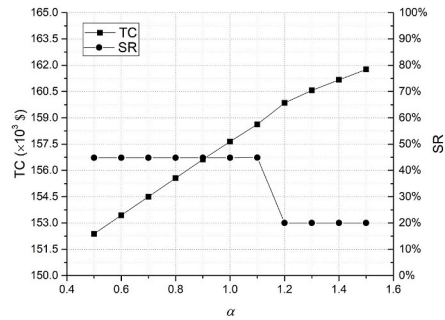


(d) Impacts on the various cost components

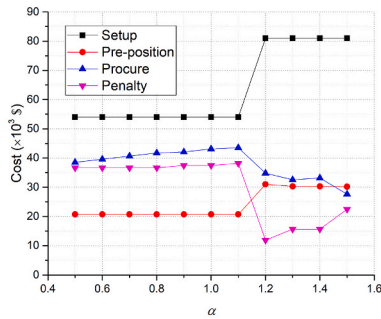
Fig. 8. Sensitivity analyses on ω



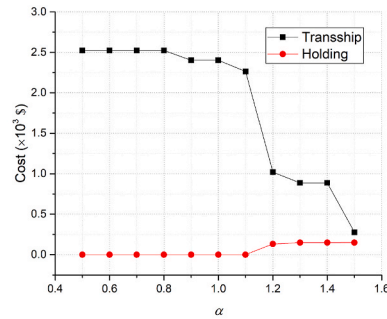
(a) Impacts on the weighted total costs



(b) Impacts on TC and SR



(c) Impacts on the various cost components



(d) Impacts on the various cost components

Fig. 9. Sensitivity analyses on τ_{ji}^s

between the two planning goals. τ_{ji}^s , the unit supply delivering cost from supplier j to member hospital i under scenario s , can be influenced by post-epidemic factors like emergency transportation cost, traffic control, traffic congestion and road damage. To examine the impacts of τ_{ji}^s , we modify the values of τ_{ji}^s via $\tau_{ji}^s = \alpha \bar{\tau}_{ji}^s, \forall j \in J, i \in I, s \in S$, where α is a modification factor, and $\bar{\tau}_{ji}^s$ are the base case values in Table 3. The sensitivity analyses results of τ_{ji}^s are illustrated in Fig. 9.

In general, Subfigures 9(a) and 9(b) point out that the increased unit supplies delivering cost boosts the weighted total cost and TC and brings SR down to a limit. Especially, Subfigure 9(b) indicates that small values of τ_{ji}^s (i.e., $\alpha \leq 1$) can reduce TC without sacrificing SR (equity), which highlights the importance of delivering procured supplies fast considering that τ_{ji}^s can be most closely related to the time value associated with the various emergency supply delivering time. In addition, Subfigures 9(c) and 9(d) show that big values of τ_{ji}^s (i.e., $\alpha \geq 1.1$) have more impacts on the various cost components of TC. Specifically, when α increases from 0.5 to 1.1, the procurement (transshipment) cost increases (decreases) slightly while the other costs are stable. However, when α increases from 1.1 to 1.5, all cost components vary significantly, indicating that more supplies are pre-stocked and fewer supplies are urgently procured and transshipped. This highlights that if the delivery of urgently procured supplies is expected to be slow and costly, the healthcare coalition should pre-stock more supplies in advance. Similarly, we investigate the impacts of ν_{ki}^s , shortage (unmet demand) cost of unit type k supply in member hospital i under scenario s , via $\nu_{ki}^s = \beta \bar{\nu}_{ki}^s, \forall k \in K, i \in I, s \in S$, where β is a modification factor and $\bar{\nu}_{ki}^s$ are the base case values in Table 4. The sensitivity analyses results of ν_{ki}^s are illustrated in Fig. 10.

In general, Fig. 10 shows that the optimal plan is more sensitive to ν_{ki}^s when the values of ν_{ki}^s are relatively small (i.e., $\beta \leq 1.1$). Sub-Fig. 10(a)

and 10(b) point out that as ν_{ki}^s increases, the weighted total cost and TC both increase with a decreasing speed and up to a limit while SR decreases suddenly. The trade-off between TC and SR is obvious when $0.9 \leq \beta \leq 1.1$. Thus, ν_{ki}^s should be set cautiously in practice, and that let the values of ν_{ki}^s be relatively high can contribute to more equity in the coalition after the epidemic. In addition, the variation trends of cost components in Subfigures 10(c) and 10(d) reveal that when β increases from 0.5 to 1, nearly all cost components increase (except the penalty and holding costs), implying that more supplies are pre-stocked, urgently procured and transshipped. However, when β continues rising from 1 to 1.5, the setup and pre-positioning costs keep increasing, but up to certain limits, while the procurement and transshipment costs slightly fall, down to certain limits. This implies that more supplies are pre-stocked in advance, but less are procured and transshipped after the epidemic. In short, Subfigures 10(c) and 10(d) suggest: 1) When the unit supply shortage cost is high, more emergency supplies should be pre-positioned, procured and transshipped before and after the epidemic; 2) As the shortage costs of unit supply increase from small (big) values, strengthening supplies pre-positioning, procurement and transshipment simultaneously can be an effective (ineffective) shortcut for enhancing the existing plan.

5. Conclusions and future work

In this work, we propose a two-stage stochastic emergency supply planning model to facilitate cooperation and coordination in a healthcare coalition. Our model decides the types and locations of deployed warehouses and the amounts of various pre-stocked emergency supplies in the healthcare coalition before disasters and determines the optimal scenario-based emergency supplies transshipment and procurement plans for the healthcare coalition after disasters. Two planning goals, i.

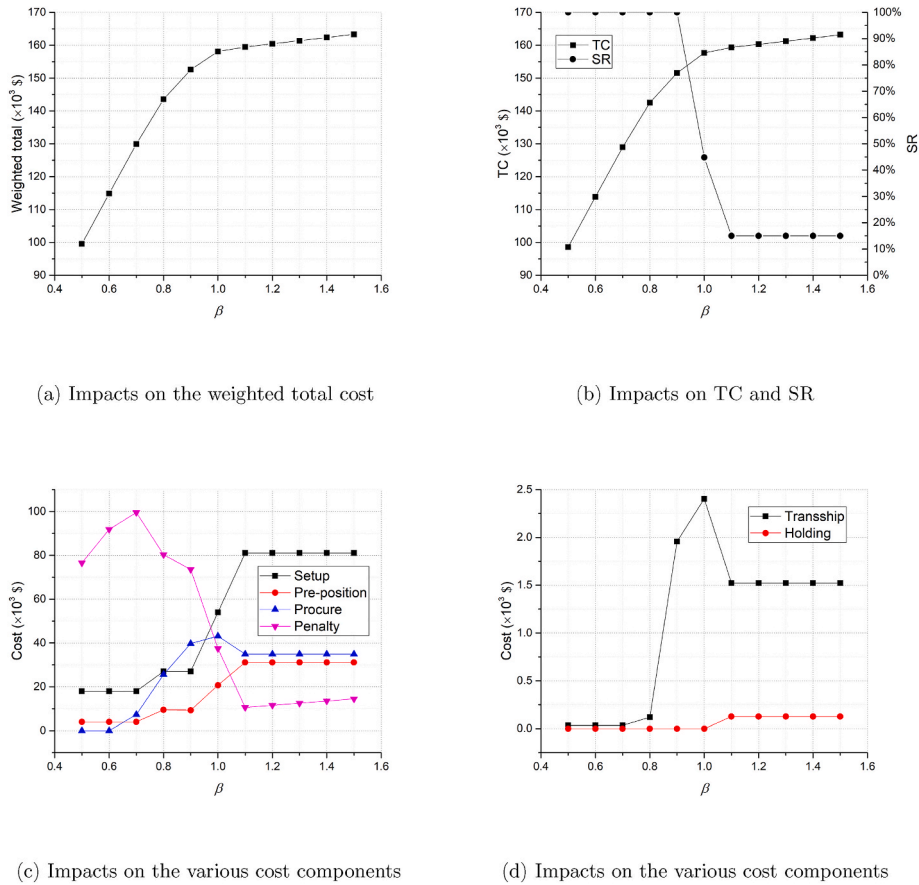


Fig. 10. Sensitivity analyses on L_{ki}^z

e., cost-effectiveness and service equity, and various uncertain factors are explicitly incorporated. With some comparison models and a case study on the WCH coalition of Sichuan Province, China, under the background of the COVID-19 epidemic, we demonstrate the effectiveness and benefits of our model and obtain various managerial insights and policy suggestions for practice, such as 1) It benefits the whole coalition via allowing AHs to pre-stock emergency supplies and conducting coordinated emergency supplies transshipment between WCH and AHs; 2) Setting up an emergency warehouse at the CH may not always be part of the optimal solution for a regional healthcare coalition; 3) If the delivering of urgently procured supplies tends to be slow and costly or the unit supply shortage cost is high, the healthcare coalition should pre-position more supplies in advance. In particular, we find it vital to conduct integrated management of emergency supplies pre-positioning, transshipment and procurement in healthcare coalitions for better preparedness and response to future potential disasters. A government should develop policies for enhancing the cooperation and coordination of emergency supplies management in healthcare coalitions.

Future work can be conducted in two aspects. First, considering that the post-disaster situation is time-varying, a multi-stage stochastic programming approach can be employed to obtain a more general and realistic solution. Second, more practical issues, such as non-linear supply shortage costs, donations of emergency supplies, and government interventions, can be further incorporated to improve the integrated emergency supplies management plans for regional healthcare coalitions in the future.

Author statement

Qingyi Wang: Conceptualization, Methodology, Programming,

Result Analyses, Writing – Original Draft, Review & Editing; **Zhuomeng Liu:** Methodology, Programming, Data Curation, Result Analyses, Writing – Original Draft; **Peng Jiang:** Result Analyses, Writing – Review & Editing; **Li Luo:** Writing – Review & Editing;

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References

- [1] Fisher D, Hagon K, Lattimer C, O’Callaghan S, Swithern S, Walmsley L. World disasters report: Leaving No one behind. 2018. <https://media.ifrc.org/ifrc/world-disaster-report-2018>, International Federation of Red Cross and Red Crescent Societies. [Accessed 30 July 2021].
- [2] Barebera J, Macintyre A. Medical surge capacity and capability: the health care coalition in emergency response and recovery. U.S. Department of Health and Human Services; 2014. <http://www.phe.gov/Preparedness/planning/mscc/healthcarecoalition/Pages/default.aspx>. [Accessed 30 July 2021].
- [3] Courtney B, Toner E, Waldhorn R, Franco C, Rambhia K, Norwood A, Inglesby TV, O’Toole T. Healthcare coalitions: the new foundation for national healthcare preparedness and response for catastrophic health emergencies. Biosecure Bioterrorism Biodefense Strategy, Pract Sci 2009;7(2):153–63.
- [4] Pereira MA, Marques RC, Ferreira DC. An incentive-based framework for analyzing the alignment of institutional interventions in the public primary healthcare sector: the Portuguese case. Healthcare 2021;9(7):904.
- [5] Pereira MA, Marques RC. Is sunshine regulation the new prescription to brighten up public hospitals in Portugal? Soc Econ Plann Sci 2022:101219.

- [6] Pereira MA, Camanho AS, Figueira JR, Marques RC. Incorporating preference information in a range directional composite indicator: the case of Portuguese public hospitals. *Eur J Oper Res* 2021;294(2):633–50.
- [7] Caunhye AM, Nie X, Pokharel S. Optimization models in emergency logistics: a literature review. *Soc Econ Plann Sci* 2012;46(1):4–13.
- [8] Özdamar L, Ertem MA. Models, solutions and enabling technologies in humanitarian logistics. *Eur J Oper Res* 2015;244(1):55–65.
- [9] Sabbaghtorkan M, Batta R, He Q. Prepositioning of assets and supplies in disaster operations management: review and research gap identification. *Eur J Oper Res* 2020;284(1):1–19.
- [10] Salas LC, Cárdenas MR, Zhang M. Inventory policies for humanitarian aid during hurricanes. *Soc Econ Plann Sci* 2012;46(4):272–80.
- [11] Galindo G, Batta R. Prepositioning of supplies in preparation for a hurricane under potential destruction of prepositioned supplies. *Soc Econ Plann Sci* 2013;47(1): 20–37.
- [12] Zhang B, Peng J, Li S. Covering location problem of emergency service facilities in an uncertain environment. *Appl Math Model* 2017;51:429–47.
- [13] Beamon BM, Kotleba SA. Inventory modelling for complex emergencies in humanitarian relief operations. *Int J Logist: Res. Appl.* 2006;9(1):1–18.
- [14] Duran S, Gutierrez MA, Keskinocak P. Pre-positioning of emergency items for CARE international. *Interfaces* 2011;41(3):223–37.
- [15] Liu K, Li Q, Zhang Z-H. Distributionally robust optimization of an emergency medical service station location and sizing problem with joint chance constraints. *Transp Res Part B Methodol* 2019;119:79–101.
- [16] Xu N, Zhang Q, Zhang H, Hong M, Akerkar R, Liang Y. Global optimization for multi-stage construction of rescue units in disaster response. *Sustain Cities Soc* 2019;51:101768.
- [17] Jin JG, Shen Y, Hu H, Fan Y, Yu M. Optimizing underground shelter location and mass pedestrian evacuation in urban community areas: a case study of Shanghai. *Transport Res Pol Pract* 2021;149:124–38.
- [18] Wang H, Du L, Ma S. Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake. *Transport Res E Logist Transport Rev* 2014;69:160–79.
- [19] Haghani A, Oh S-C. Formulation and solution of a multi-commodity, multi-modal network flow model for disaster relief operations. *Transport Res Pol Pract* 1996;30(3):231–50.
- [20] Barbarosoğlu G, Arda Y. A two-stage stochastic programming framework for transportation planning in disaster response. *J Oper Res Soc* 2004;55(1):43–53.
- [21] Horner MW, Downs JA. Optimizing hurricane disaster relief goods distribution: model development and application with respect to planning strategies. *Disasters* 2010;34(3):821–44.
- [22] Lin Y-H, Batta R, Rogerson PA, Blatt A, Flanigan M. A logistics model for emergency supply of critical items in the aftermath of a disaster. *Soc Econ Plann Sci* 2011;45(4):132–45.
- [23] Rivera-Royero D, Galindo G, Yie-Pinedo R. A dynamic model for disaster response considering prioritized demand points. *Soc Econ Plann Sci* 2016;55:59–75.
- [24] Liu M, Zhang D. A dynamic logistics model for medical resources allocation in an epidemic control with demand forecast updating. *J Oper Res Soc* 2016;67(6): 841–52.
- [25] Fragkos ME, Zeimpekis V, Koutras V, Minis I. Supply planning for shelters and emergency management crews. *Oper. Res.* 2020:1–37.
- [26] Safaei AS, Farsad S, Paydar MM. Emergency logistics planning under supply risk and demand uncertainty. *Oper. Res.* 2020;20(3):1437–60.
- [27] Yin X, Büyüktaktakın İE. A multi-stage stochastic programming approach to epidemic resource allocation with equity considerations. *Health Care Manag Sci* 2021:1–26.
- [28] Chang M-S, Tseng Y-L, Chen J-W. A scenario planning approach for the flood emergency logistics preparation problem under uncertainty. *Transport Res E Logist Transport Rev* 2007;43(6):737–54.
- [29] Rawls CG, Turnquist MA. Pre-positioning of emergency supplies for disaster response. *Transp Res Part B Methodol* 2010;44(4):521–34.
- [30] Mete HO, Zabinsky ZB. Stochastic optimization of medical supply location and distribution in disaster management. *Int J Prod Econ* 2010;126(1):76–84.
- [31] Döyen A, Aras N, Barbarosoğlu G. A two-echelon stochastic facility location model for humanitarian relief logistics. *Optim. Lett.* 2012;6(6):1123–45.
- [32] Noyan N. Risk-averse two-stage stochastic programming with an application to disaster management. *Comput Oper Res* 2012;39(3):541–59.
- [33] Caunhye AM, Zhang Y, Li M, Nie X. A location-routing model for prepositioning and distributing emergency supplies. *Transport Res E Logist Transport Rev* 2016; 90:161–76.
- [34] Manopiniwes W, Irohara T. Stochastic optimisation model for integrated decisions on relief supply chains: preparedness for disaster response. *Int J Prod Res* 2017;55(4):979–96.
- [35] Paul JA, Zhang M. Supply location and transportation planning for hurricanes: a two-stage stochastic programming framework. *Eur J Oper Res* 2019;274(1): 108–25.
- [36] Wang Q, Nie X. A stochastic programming model for emergency supply planning considering traffic congestion. *IIEE Trans.* 2019;51(8):910–20.
- [37] Hu S, Dong ZS. Supplier selection and pre-positioning strategy in humanitarian relief. *Omega* 2019;83:287–98.
- [38] Wang Q, Nie X. A stochastic programming model for emergency supply planning considering transportation network mitigation and traffic congestion. *Soc Econ Plann Sci* 2021:101119.
- [39] Wang Y, Dong ZS, Hu S. A stochastic prepositioning model for distribution of disaster supplies considering lateral transshipment. *Soc Econ Plann Sci* 2021;74: 100930.
- [40] Sancı E, Daskin MS. An integer L-shaped algorithm for the integrated location and network restoration problem in disaster relief. *Transp Res Part B Methodol* 2021; 145:152–84.
- [41] Tzeng G-H, Cheng H-J, Huang TD. Multi-objective optimal planning for designing relief delivery systems. *Transport Res E Logist Transport Rev* 2007;43(6):673–86.
- [42] Sheu J-B, Pan C. A method for designing centralized emergency supply network to respond to large-scale natural disasters. *Transp Res Part B Methodol* 2014;67: 284–305.
- [43] Rambhia KJ, Waldhorn RE, Selck F, Mehta AK, Franco C, Toner ES. A survey of hospitals to determine the prevalence and characteristics of healthcare coalitions for emergency preparedness and response. *Biosecure Bioterrorism Biodefense Strategy, Pract Sci* 2012;10(3):304–13.
- [44] Devereaux A, Yang H, Seda G, Sankar V, Maves RC, Karanjia N, Parrish JS, Rosenberg C, Goodman-Crews P, Cederquist L, et al. Optimizing scarce resource allocation during COVID-19: rapid creation of a regional health-care coalition and triage teams in san Diego County, California. *Disaster Med Public Health Prep* 2020:1–7.
- [45] Cao Y, Li Q, Chen J, Guo X, Miao C, Yang H, Chen Z, Li C, Li L. Hospital emergency management plan during the COVID-19 epidemic. *Acad Emerg Med* 2020;27(4): 309–11.

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