

Invited paper

A stochastic prepositioning model for distribution of disaster supplies considering lateral transshipment

Yusheng Wang^a, Zhijie Sasha Dong^{b,*}, Shaolong Hu^c

^a School of Management Science and Engineering, Nanjing University of Information Science & Technology, Nanjing, 210044, PR China

^b Texas State University, 601 University Drive, San Marcos, TX, 78666, USA

^c School of Economics and Management, Southwest Jiaotong University, Chengdu, PR China

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ABSTRACT

This paper focuses on addressing uncertainties in disasters when considering lateral transshipment opportunities for pre-positioning relief supplies. To deal with uncertain demands the problem is formulated as a two-stage stochastic programming model, which decides simultaneously on the locations of relief facilities and the allocations of relief supplies to demand nodes. Meanwhile, different damage levels caused by disasters are considered and reflected by a survival rate of usable stocked relief items. Multiple types of supplies with various priorities, values and spaces are explored. A real-world case study based on the Gulf Coast region of the United States is conducted to illustrate the application of the developed model. By comparison with the direct shipment solution, the lateral transshipment solution is demonstrated to be more cost-effective and flexible. The sensitivity analysis of out-of-stock penalty cost and maximum travel distance provides managerial insights for relief agencies.

1. Introduction

The world is frequently affected by natural disasters, which typically cause catastrophic consequences for humanity. According to the most recent statistics from the Centre for Research on the Epidemiology of Disasters (CRED), there were 315 climate-related and geophysical disaster events recorded in 2018 with 11,804 deaths and \$131.7 billion in damages, and over 68 million people affected across the world [1]. A recent example is the hurricanes Florence and Michael that successively occurred in September and October in 2018, which caused more than 120 deaths and \$50 billion in economic losses, and the vast eastern coastal states of the United States from north to south were affected. These facts reveal the importance of disaster management in mitigating the negative effects of disasters [2]. Disaster management can be divided into four phases, namely, mitigation, preparedness, response and recovery [3,4]. This research mainly deals with two types of decisions: storing relief supplies in advance at storage facilities before a disaster occurs and distribution of these items from storage facilities to affected communities right after a disaster occurs. Therefore it can be classified within the preparedness and response phrases.

In the preparedness phase, one of the strategies that are commonly applied upon the occurrence of a disaster is to pre-position relief

commodities (e.g., water and food) at strategic locations so that these supplies are readily available and can be delivered to affected communities as soon as possible once natural disasters strike [5]. On one hand, inadequate relief items and/or untimely delivery will cause ineffective emergency response, and thus resulting in the increase in human suffering and even loss of life. On the other hand, over-investment in stock of relief commodities would incur very high inventory costs and occupy too much public funds. Therefore, it is cost-effective to estimate the demands for the relief supplies at affected community. However, because of the unpredictable nature of disasters (e.g., occurrence frequency and location), demand for relief supplies is highly uncertain, and most of the time it is difficult to make pre-positioning decisions.

The “traditional” logistics systems are usually considered to be hierarchical, where commodities are transported from one echelon to the next, i.e. manufacturers, wholesalers, retailers etc. Due to the uncertainty of demand, the commodities may be in short at some locations while abundant at other locations. To alleviate the mismatch between an actual demand and an available stock in strategy locations under the inability to replenish from a central warehouse, the practice of allowing horizontal transportation within the same echelon, namely, *lateral transshipment* was proposed [6]. Lateral transshipment is mostly applied in the commercial logistics systems, especially for low-demand,

* Corresponding author.

E-mail address: sasha.dong@txstate.edu (Z.S. Dong).

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high-value items (e.g. spare parts) in emergency orders. As slow-moving expensive items, spare parts require a quick response to an infrequent demand. Lateral transshipment allows for an additional source of procurement from a nearby location once a stockout of spare parts occurs. This leads to cost reduction and service improvement compared to networks without lateral transshipment.

Considering the nature of emergency and infrequency in the humanitarian logistics, lateral transshipment can also be an appropriate and efficient alternative to alleviating the suffering of victims within the shortest possible time. When lateral transshipment is applied in the humanitarian logistics, a storage facility can obtain the relief supplies from a nearby facility if it cannot satisfy the immediate need of victims from its own inventory. This strategy can reduce the burden of pre-positioning more relief supplies with high inventory cost at the storage facilities or waiting for the next shipment from upper agencies. However, due to the uncertainty of natural disasters and the non-profit nature of humanitarian relief, the importance of lateral transshipment has not been recognized much in the field of humanitarian logistics and the relevant literature is scarce.

In this paper, we develop a two-stage stochastic programming model to make integrated decisions on facility location, stocking levels for relief supplies, and distribution of those supplies to demand locations including lateral transshipment after a disaster, with uncertainty in demand. In the first stage (i.e., the preparedness phrase), decision variables include the location and size of storage facilities, as well as amounts of relief supplies pre-positioned at the facilities. These decisions have to be made in the presence of uncertainty about future demands. In the second stage (i.e., the response phrase), decision variables involve the distribution of available relief supplies to demand locations by direct shipment or lateral transshipment. These decisions are made after the realization that the uncertainty is known, and are conditional on the first-stage decisions. The developed model aims to make the optimal first-stage decisions, under uncertainty about the conditions to be faced in the second stage.

The major contributions of this paper are summarized as follows:

- The lateral transshipment option is incorporated into the pre-positioning humanitarian logistics. The relief supplies can be transported directly from relief facilities to demand locations (i.e., direct shipment), or through other relief facilities (i.e., lateral transshipment). The biggest advantage of the lateral transshipment network over the one without lateral transshipment is its flexibility in replenishing of supplies. This advantage is particularly significant when demands for relief supplies are uncertain.
- We consider two aspects of uncertainty for a disaster: the uncertain demand for relief supplies and the uncertainty of the damage degree to the supplies pre-positioned at the relief facilities. The stock of relief supplies pre-positioned at the relief facilities may be destroyed or partially damaged by a disaster, which determines the available amount of supplies for disaster relief. In this study, a set of scenarios are used to characterize the possible disasters, and the extent of damage caused by the disasters to the relief supplies pre-positioned at the facilities is taken into account when defining the scenarios.
- The problem studies multiple types of relief supplies rather than only one single type. In practice, various types of relief supplies are needed aftermath of a disaster, and these supplies have different values and priorities, as well as occupying spaces. Therefore, how to coordinate and manage multiple types of relief materials is also a research focus in this paper.

The rest of the paper is organized as follows. Relevant literature is reviewed in Section 2. In Section 3, the problem is described and the mathematical models are developed for both direct shipment and lateral transshipment cases. In Section 4, a case study is presented and the sensitivity analysis is conducted. Finally, we conclude our work and discuss possible future research directions in Section 5.

2. Literature review

The relevant literature can be categorized into two major groups: pre-positioning strategy in disaster response and lateral transshipment problem.

2.1. Pre-positioning strategy in disaster response

Pre-positioning of relief supplies is an effective strategy to help relief agencies improve their capacity of preparedness and emergency response to various natural disasters. The literature on the pre-positioning of relief supplies is relatively rich. For example, Rawls and Turnquist [7] was the first to present a two-stage stochastic mixed integer programming model in determining relief facility locations and quantities of various types of relief supplies to be pre-positioned at the relief facilities while considering the uncertainty about disasters and the availability of the transportation network. Duran et al. [8] evaluated the effect that pre-positioning relief items would have on the average relief-aid emergency response time for CARE International. Galindo and Batta [9] developed a model to investigate the pre-positioning of supplies in preparation for a hurricane under potential destruction of pre-positioned supplies. Rezaei-Malek et al. [10] developed an integrated model for designing a robust disaster relief logistics network with perishable commodities. Chen et al. [11] developed a two-stage delivery process model to characterize relief materials' delivery after a disaster, in which storage materials are delivered in the first stage and all backlogged demands are satisfied in the second stage. Ni et al. [12] proposed a min-max robust model to simultaneously optimize the decisions of facility location, emergency inventory pre-positioning, and relief delivery operations within a single-commodity disaster relief network. Hu and Dong [13] presented a two-stage stochastic programming model to address the joint decision-making of pre-positioning of relief supplies and supplier selection under disruption risks in humanitarian relief. More work related to the pre-positioning of relief supplies can refer to the review paper by Sabbaghtorkan et al. [14].

Pre-positioning problems usually involve decision-making for both preparedness and response phrases of disaster management. To be more specific, these decisions include determining the level of preparedness (e.g. location and inventory level of relief supplies) in the pre-disaster phase, and then distribution of relief supplies to affected community in the post-disaster phase [15,16]. Thus, two-stage stochastic programming is one of the most commonly-used methodology, which is powerful to handle uncertainty by using probabilistic scenarios to represent disasters and their consequences.

2.2. Lateral transshipment

Lateral transshipment has been widely studied in commercial logistics. Most of the commercial lateral transshipment research is related to the low-demand and high-value commodities (e.g., spare parts). Wong et al. [17] developed a multi-item, continuous review model of two-location inventory systems for repairable spare parts. Olsson [18] investigated the application of lateral transshipment in a single-echelon continuous review inventory system for spare parts with two parallel locations. Meissner and Senicheva [19] developed an approximate dynamic programming model to examine multi-location inventory systems under periodic review with multiple opportunities for lateral transshipment within one order cycle. Avci [20] presented a mean-CVaR approach to investigate the effects of lateral transshipment and expedited shipping on supply chain performance in a retail system with multiple distribution centers and multiple retailers. Wijk et al. [21] investigated the optimal lateral transshipment policies for a two location inventory problem with multiple demand classes.

Different from commercial logistics, humanitarian logistics mainly involve a surge of demand for relief supplies with low value, such as bottled water, tents, food etc. There has been few literature on lateral

transshipment in humanitarian logistics. The practice of lateral transshipment in humanitarian logistics can be sourced from Lodree et al. [22], where supplies were transshipped among retailers to satisfy the unfulfilled demands. Later on, Rottkemper et al. [23] developed a transshipment model for distribution and inventory relocation under uncertainty in humanitarian operations. Caunhye et al. [24] developed a location-routing model with recourse for integrated preparedness and response planning under uncertainty, and transshipment was incorporated into the model. Baskaya et al. [25] developed three mathematical models (i.e., direct shipment model, lateral transshipment model and maritime lateral transshipment model) to investigate the inclusion of lateral transshipment opportunities into the humanitarian relief chain. Coskun et al. [26] developed a mathematical model that takes cooperation between agencies into consideration to characterize stock-prepositioning decisions of relief agencies.

2.3. Research distinction

As discussed above, the two-stage stochastic programming approach has been proposed to address both preparedness and response decisions. However, most of these decisions do not consider the lateral transshipment option. Moreover, the lateral transshipment is usually discussed in the commercial logistics and there is rare literature on the inclusion of lateral transshipment into the humanitarian logistics. Furthermore, the limited literature on the lateral transshipment in humanitarian logistics didn't consider the diversity of relief supplies as well as the destructive effect of natural disasters on the relief supplies pre-positioned at the relief facilities. To fill these research gaps, we develop a two-stage stochastic programming model to incorporate the lateral transshipment option into the humanitarian logistics. The relief supplies can be transported directly from relief facilities to demand locations (i.e., direct shipment), or through other relief facilities (i.e., lateral transshipment). Our model considers the uncertain demand for relief supplies and the destructive effect of natural disasters on the relief supplies pre-positioned at the relief facilities. Furthermore, the diversity of relief supplies is also considered in our study.

3. Modeling

3.1. Problem description

We consider a humanitarian logistics system consisting of two echelons, namely, storage facilities and demand points, as shown in Fig. 1. We assume that storage facilities are willing to share sufficient and reliable information about their current inventories with other storage facilities. At the planning stage, the demand for relief supplies at a certain location is uncertain, since it is not yet known whether, or where a disaster will occur. The uncertainty can be presented by a set of discrete scenarios, which can be defined using the location and the scale of a disaster, as well as the demand for each type of relief supply [7,13].

To react to the possible natural disasters as soon as possible, a certain amount of relief supplies should be pre-positioned at storage facilities. A fixed cost will be incurred if a storage facility is made available. Meanwhile, the quantity of the relief supplies pre-positioned must not

exceed the capacity of the storage facilities. In addition, part or all of the relief supplies pre-positioned at a given storage facility may be destroyed by the disaster, which is affected by the scale and the location of disasters. The degree of damage can be represented by a parameter, called survival rate, which is also a part of the scenario definitions.

After a disaster occurs, the survived stocks of the relief supplies in the storage facilities are distributed across a transportation network to meet demands in the affected community. There are two types of material shipments: direct shipment and lateral transshipment, as shown in Fig. 1. Direct shipment is defined as the situations where relief supplies are transported from storage facilities to demand nodes. Each demand node is assigned to only one storage facility and the stocks on hand are used to satisfy the assigned demands first. If there is an excess inventory, the holding cost will be incurred. On the other hand, if the demand for a particular relief commodity cannot be satisfied, a penalty cost for the shortage of this commodity will be incurred. In addition, lateral transshipment between storage facilities is also possible. If a storage facility cannot satisfy the assigned demand using its own stock on hand, it may "borrow" the excess stock from other storage facilities, which would incur a lateral transshipment cost. For each storage facility, it is allowed to use at most one other facility for lateral transshipment. The decision-makers need to balance the out-of-stock penalty cost, holding cost and the lateral transshipment cost.

This study aims to identify an optimal strategy that combines decisions on storage facility locations, stocking levels for relief supplies, and distribution of those relief supplies to multiple demand points after a disaster, with uncertainty in demand and usable pre-positioned stocks of relief supplies.

3.2. Direct shipment model

To model the problem described above, a direct shipment model (P_0) without considering lateral transshipment should be developed first. The direct shipment problem can be formulated as a two-stage stochastic mixed integer programming model. In the first stage, the decision variables include the location and size of storage facilities, as well as amounts of relief supplies pre-positioned at the facilities. These decisions have to be made in the presence of uncertainty about future demands. In the second stage, the decision variables involve the distribution of available relief supplies in response to specific scenario disasters. These decisions are made after the realization that the uncertainty is known, and are conditional on the first-stage decisions. The notations for the direct shipment model are presented as follows.

Sets:

- I Set of candidate locations for relief storage facility, indexed by i ;
- J Set of demand locations, indexed by j ;
- K Set of types of relief commodities, indexed by k ;
- L Set of size categories of relief storage facilities, indexed by l ;
- S Set of possible disaster scenarios, indexed by s .

Parameters:

- Q_j^{ks} Demand for commodity k at location j in scenario s ;
- P_s Occurrence probability of scenario s ;
- D_{ij} Distance between location i and location j ;
- R Maximum distance that a relief commodity can travel;
- Θ_l Storage capacity of a relief facility of category l ;
- ρ^k Unit storage space requirement for commodity k ;
- FC_{il} Unit fixed cost incurred by opening a relief facility of size category l in location i ;
- AC^k Unit procurement cost for commodity k ;
- TC_s^k Unit transport cost for commodity k per kilometer in scenario s ;
- PC_s^k Unit penalty cost for the shortage of commodity k in scenario s ;
- HC_s^k Unit holding cost for surplus of commodity k in scenario s ;
- LC_s^k Unit operational cost to process the lateral transshipment for commodity k in scenario s ;
- ρ_i^{ks} Proportion of stocked relief commodity k at location i remaining useable after a disaster in scenario s ;
- M A big enough positive number.

First-Stage Decision Variables:

(continued on next page)

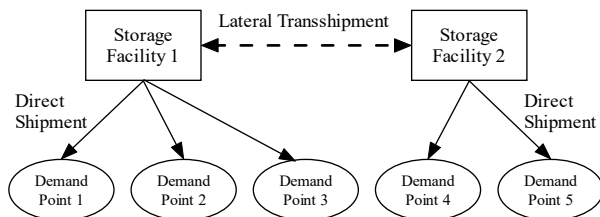


Fig. 1. Relief items flow in the humanitarian logistics system.

(continued)

y_{il}	Binary decision variable which indicates whether a relief facility of capacity category l is built at location i (value 1) or not (value 0);
q_i^k	Quantity of relief commodity k pre-positioned at location i ;
Second-Stage Decision Variables:	
x_{ij}^{ks}	Quantity of commodity k transported from relief facility i to demand location j in scenario s ;
z_{ij}^s	Binary decision variable which indicates whether demand location j is assigned to relief facility i in scenario s (value 1) or not (value 0);
Auxiliary Decision Variables:	
u_j^{ks}	Unsatisfied demand of commodity k at demand location j in scenario s ;
v_i^{ks}	Surplus quantity of commodity k at facility location i in scenario s .

The complete direct shipment model (P_0) is formulated as below.

$$(P_0) \min C = \sum_{i \in I} \sum_{l \in L} FC_{il} y_{il} + \sum_{k \in K} \sum_{i \in I} AC^k q_i^k + \sum_{s \in S} \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} P_s (TC_s^k D_{ij} x_{ij}^{ks} + PC_s^k u_j^{ks} + HC_s^k v_i^{ks}) \quad (1)$$

Subject to:

$$\sum_{i \in I} x_{ij}^{ks} = Q_j^{ks} - u_j^{ks} \quad \forall j \in J, k \in K, s \in S \quad (2)$$

$$\sum_{j \in J} x_{ij}^{ks} + v_i^{ks} = \rho_i^{ks} \cdot q_i^k \quad \forall i \in I, k \in K, s \in S \quad (3)$$

$$D_{ij} \cdot z_{ij}^s \leq R \quad \forall i \in I, j \in J, s \in S \quad (4)$$

$$\sum_{k \in K} \theta^k \cdot q_i^k \leq \sum_{l \in L} \Theta_l \cdot y_{il} \quad \forall i \in I \quad (5)$$

$$\sum_{l \in L} y_{il} \leq 1 \quad \forall i \in I \quad (6)$$

$$\sum_{i \in I} z_{ij}^s = 1 \quad \forall s \in S, j \in J \quad (7)$$

$$\sum_{j \in J} z_{ij}^s \leq \sum_{l \in L} M \cdot y_{il} \quad \forall i \in I, s \in S \quad (8)$$

$$x_{ij}^{ks} \leq M \cdot z_{ij}^s \quad \forall i \in I, j \in J, k \in K, s \in S \quad (9)$$

$$x_{ij}^{ks}, u_j^{ks}, v_i^{ks}, q_i^k \geq 0 \quad \forall i \in I, j \in J, k \in K, s \in S \quad (10)$$

$$y_{il}, z_{ij}^s \in \{0, 1\} \quad \forall i \in I, j \in J, k \in K, l \in L, s \in S \quad (11)$$

The objective function (1) minimizes the expected costs over all scenarios resulting from the selection of the pre-positioning locations and facility sizes, the commodity procurement and stocking decisions, the shipments of the supplies to the demand points, unmet demand penalties and holding costs for unused material. Constraints (2) and (3) define the flow conservations in the network at each demand location and relief facility, for every commodity and every scenario. These two conservations of flow indirectly define the unmet demand and the unused stocks, respectively. Constraint (4) limits the travel distance of relief items. Due to the emergency nature of disaster relief, the relief supplies usually need to be delivered to demand points as soon as possible. The requirement for the time spent on the road limits the maximum travel distance. Constraint (5) makes sure that stocked commodities are assigned to opened facilities and that the space taken by these resources does not exceed the facility capacity. Constraint (6) limits the number of open facilities at node i to at most one. Constraint

(7) guarantees that each demand location j is assigned to only one relief facility. Constraint (8) ensures that a demand location only can be assigned to a relief facility that is opened. Constraint (9) ensures that relief commodities cannot be sent from a relief facility to a demand location unless that demand location is assigned to that relief facility. Constraints (10) and (11) define restrictions on decision variables.

3.3. Model considering lateral transshipment

When the lateral transshipment option is considered, the model can be developed on the basis of the direct shipment model (P_0). A new index i' under the set I is introduced to denote the relief facilities used as lateral transshipment source. In addition to the parameters and decision variables used in the direct shipment model, a new parameter LC_s^k is

used to denote the unit operational cost to process the lateral transshipment for commodity k in scenario s . The additional decision variables are defined as follows:

$\bar{x}_{i'ij}^{ks}$: Quantity of commodity k transported from relief facility i to demand location j through facility i' in scenario s ;

$f_{i'ij}^s$: Binary decision variable which indicates whether the supplies are transported from facility i to demand location j through lateral transshipment node i' in scenario s (value 1) or not (value 0).

Then the complete lateral transshipment model (P_1) can be developed as below.

$$(P_1) \min C' = \sum_{i \in I} \sum_{l \in L} FC_{il} y_{il} + \sum_{k \in K} \sum_{i \in I} AC^k q_i^k + \sum_{s \in S} P_s \left\{ \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} TC_s^k D_{ij} x_{ij}^{ks} + \sum_{i, i' \in I: i' \neq i} \sum_{j \in J} \sum_{k \in K} [TC_s^k (D_{i'j} + D_{ij}) + LC_s^k] \bar{x}_{i'ij}^{ks} + \sum_{k \in K} \sum_{j \in J} PC_s^k u_j^{ks} + \sum_{k \in K} \sum_{i \in I} HC_s^k v_i^{ks} \right\} \quad (12)$$

Subject to:

Constraints (4)–(11)

$$\sum_{i \in I} x_{ij}^{ks} + \sum_{i, i' \in I: i' \neq i} \bar{x}_{i'ij}^{ks} = Q_j^{ks} - u_j^{ks} \quad \forall j \in J, k \in K, s \in S \quad (13)$$

$$\sum_{j \in J} x_{ij}^{ks} + \sum_{j \in J} \sum_{i' \in I \setminus \{i\}} \bar{x}_{i'ij}^{ks} + v_i^{ks} = \rho_i^{ks} \cdot q_i^k \quad \forall i \in I, k \in K, s \in S \quad (14)$$

$$(D_{i'j} + D_{ij}) \cdot f_{i'ij}^s \leq R \quad \forall i, i' \in I, i' \neq i, j \in J, s \in S \quad (15)$$

$$\bar{x}_{i'ij}^{ks} \leq M \cdot f_{i'ij}^s \quad \forall i, i' \in I, i' \neq i, j \in J, k \in K, s \in S \quad (16)$$

$$\sum_{j \in J} \sum_{i' \in I \setminus \{i\}} f_{i'ij}^s \leq \sum_{l \in L} M \cdot y_{il} \quad \forall i \in I, s \in S \quad (17)$$

$$\sum_{j \in J} \sum_{i' \in I \setminus \{i\}} f_{i'ij}^s \leq \sum_{l \in L} M \cdot y_{i'l} \quad \forall i' \in I, s \in S \quad (18)$$

$$\sum_{i' \in I \setminus \{i\}} f_{i'ij}^s \leq z_{ij}^s \quad \forall i' \in I, j \in J, s \in S \quad (19)$$

$$\bar{x}_{i'ij}^{ks} \geq 0 \quad \forall i, i' \in I, i' \neq i, j \in J, k \in K, s \in S \quad (20)$$

$$f_{i'ij}^s \in \{0, 1\} \quad \forall i, i' \in I, i' \neq i, j \in J, s \in S \quad (21)$$

The objective function (12) again minimizes the expected costs over

all scenarios resulting from the selection of the pre-positioning locations and facility sizes, the commodity procurement and stocking decisions, the shipments of the supplies to the demand points, additional cost incurred by lateral transshipment, unmet demand penalties and holding costs for unused material. Constraints (13) and (14) define the flow conservations in the network at each demand location and relief facility, for every commodity and every scenario. These two conservations of flow indirectly define the unmet demand and the unused stocks, respectively. Constraints (4) and (15) limit the travel distance of relief items. Constraint (16) ensures that relief item cannot be sent through a relief facility unless lateral transshipment is allowed. Constraints (17)–(18) allow only the open relief facility pairs to engage in lateral transshipment. Constraint (19) gives the priority order between the direct shipment and lateral transshipment. When $z_{ij}^s = 1$, the demand at node j will be met first by the relief supplies pre-positioned at facility node i ; if the stock at facility node i is insufficient for the demand at node j , it will “borrow” the excess stock from facility node i , i.e. $f_{ij}^s = 1$. Constraints (20)–(21) define restrictions on decision variables.

4. Case study

In this section, a case study based on real-world hurricanes in the Gulf of Mexico region of the southeastern United States is used to illustrate the two-stage stochastic programming model as well as provide managerial implications.

4.1. Data preparation

The case study is designed based on the research network from the work of Rawls and Turnquist [7], and 15 nodes were selected as demand locations as well as candidate locations for storage facilities, as shown in Fig. 2. Table 1 lists the index and the corresponding location name of these nodes. Therefore, sets I and J both contain 15 locations. Distances between each pair of nodes were obtained using Google Distance Matrix API. For the sake of simplicity, the distance between a facility to the demand location at the same node is assumed to be 0. The maximum distance for relief commodities to travel is assumed to be 500 miles, which ensures that nearly half of the demand points can be covered by one storage facility, no matter where the facility is located.

Three emergency commodities are considered here: drinking water, food, and medicine. The unit of drinking water is assumed to be 1000 gallons. Food is assumed to be in the form of meals-ready-to-eat (MREs) and its unit is 1000 meals. Medicine is designed to be in the form of first-

Table 1

Node indices and the corresponding location names.

Index	Location	Index	Location	Index	Location
1	Brownsville, TX	6	Shreveport, LA	11	Tallahassee, FL
2	Corpus Christi, TX	7	Beaumont, TX	12	Orlando, FL
3	San Antonio, TX	8	Baton Rouge, LA	13	Tampa, FL
4	Houston, TX	9	New Orleans, LA	14	Miami, FL
5	Jackson, MS	10	Mobile, AL	15	Key West, FL

Table 2

Unit storage volume occupied, purchase price and transportation cost for each commodity.

Commodity	$\theta(\text{ft}^3)$	AC(\$)	TC (\$/mile)
Water (1000 gals)	144.6	647.7	0.3
Food (1000 meals)	83.33	5420	0.04
Medicine	1.16	140	5.80E-04

Table 3

Categories, fixed costs, and storage capacity of facilities.

Size category	Descriptor	Fixed cost (\$)	Storage capacity (ft^3)
1	Small	19,600	36,400
2	Medium	188,400	408,200
3	Large	300,000	780,000

aid kits. The values of storage volume occupied, purchase price and transportation costs for commodities in Table 2, and categories, fixed costs and storage capacity of facilities in Table 3 are from the work of Rawls and Turnquist [7]. Moreover, the unit transshipment cost for each commodity is assumed to be 1% of the purchase price, the unit holding costs are assumed to be 25% of the purchase price, and the unit penalty costs are assumed to be 10 times the purchase price. For the sake of simplicity, we assume that some parameters are scenario independent, including unit direct shipment cost, unit lateral transshipment cost, unit holding cost, and unit penalty cost for not satisfying demand for supplies. The values of these parameters are designed to be relatively realistic, but should only be regarded as the illustrative purpose.

According to the statistics from the Atlantic Oceanographic and



Fig. 2. The network for the case study.

Meteorological Laboratory (AOML), a total of 281 hurricanes struck the Gulf of Mexico region between 1851 and 2018, and these hurricanes can be classified into five categories based on the Saffir-Simpson Scale. The numbers of hurricanes for categories 1 to 5 are 118, 77, 62, 20 and 4, respectively. Thus, the frequencies of hurricanes for categories 1 to 5 can be estimated to be 0.4199, 0.274, 0.2206, 0.0712 and 0.0142, respectively. Based on historical records, three hurricanes for each category are used to construct scenarios to represent potential demands and damage in the network. Therefore, the occurrence probability of each scenario can be estimated by dividing the frequency of the corresponding category by 3. Table 4 summarizes the scenario definitions, which specify the network damage and the total demands for water, food and medicine. The detailed demands data under each scenario can be found in Mendeley data. In these scenarios, the relief commodities stocked at the landfall nodes are assumed to be damaged, and the damage degree is proportional to the Saffir-Simpson Hurricane Scale. Specifically, for a hurricane scale of category 1, 20% of the relief supplies pre-positioned at the landfall node are damaged; when the hurricane scale increases by one level, the damage degree would increase by 20%; when the hurricane scale reaches category 5, all relief supplies pre-positioned at the landfall nodes would be destroyed.

4.2. Baseline results

The established lateral transshipment model (P_1) was programmed in AMPL and solved using the commercial solver CPLEX 12.4. All numerical experiments were run on a laptop with Intel i7-8550U CPU and 8 GB of RAM under a Windows 10 environment. For comparison purposes, the results of the lateral transshipment problem (P_1) will be used as baseline results when evaluating the results of direct shipment model (P_0), where lateral transshipment is not allowed.

For the lateral transshipment problem (P_1), there are 208,155 constraints and 203,940 variables (including 6150 binary variables), which was solved in about 156 s of CPU time. The results of first-stage decision variables in the lateral transshipment problem are summarized in Table 5. A total of five storage facilities are opened, distributed widely across the network, which ensures that each demand point can be covered geographically by at least one facility within the maximum travel distance. Four of the five facilities store all three commodity types, and one facility in Mobile only stores food and medicine. Moreover, the selection of storage locations needs to balance the demand for relief supplies and the damage degree by hurricanes. For instance, New Orleans and Miami are not selected as the facility locations although the demands in both cities are much higher than those selected five locations since both of the two cities are very prone to hurricanes. In addition, the space utilization rate of facilities in east region is relatively

Table 5

Results of first-stage decision variables in baseline version.

Node	City	Facility size	Water (1000 gals)	Food (1000 meals)	Medicine	Space utilization rate
4	Houston	Small	84	110	104	58.88%
8	Baton Rouge	Medium	1078	386	513	46.21%
10	Mobile	Small	0	209	104	48.18%
11	Tallahassee	Medium	1455	1281	1314	78.07%
12	Orlando	Large	5222	297	187	100%
Total =			7839	2283	2222	

Table 6

The lateral transshipment activities in the baseline solution.

Scenario	Lateral transshipment activities		
	Water	Food	Medicine
1		(8,4,2,28), (8,4,3,40)	
2	(4,8,9,14)		
3		(10,8,5,1)	
5		(8,4,3,62), (10,8,4,13), (10,8,5,1)	(8,4,3,60)
6		(11,10,9,1281)	(11,10,9,1314)
7	(11,12,14,636)	(11,12,13,180), (11,12,14,907)	(11,12,13,266), (11,12,14,864)
8	(11,12,13,635)	(11,12,13,180), (11,12,14,907)	(11,12,13,266), (11,12,14,864)
9	(11,12,13,636)	(11,12,13,180), (11,12,14,907)	(11,12,13,449), (11,12,14,681)
10	(4,8,9,8), (11,12,13,407)	(4,8,9,74), (11,12,13,175), (11,12,14,702)	(4,8,9,70), (11,12,13,449), (11,12,14,386)
11		(4,8,9,3), (11,12,14,711)	(4,8,9,104), (11,12,14,1314)
12	(11,10,9,1133)	(11,10,9,1179), (11,12,14,102)	(11,10,9,1127)
15	(4,8,9,117)	(4,8,9,107)	(4,8,9,92)

* The four numbers in parentheses represent the original facility node, the transshipment facility node, demand node and quantity of commodities engaged in the lateral transshipment, respectively.

higher than those in west region, especially in Orlando, whose space utilization rate reaches up to 100%. The very high space utilization in Orlando is due to Florida is quite hurricane-prone area. Even if we preposition much more relief supplies there, most of them could be damaged.

Regarding the decisions made in the second stage, the relief supplies are distributed by either direct shipment or lateral transshipment. In

Table 4
Scenario definitions.

Scenario	Hurricane	Category	Landfall node	Occurrence probability	Water demand (1000 gals)	Food demand (1000 meals)	Medicine demand (units)
1	1	1	4	0.14	310	465	443
2	2	1	9	0.14	1275	138	306
3	3	1	9	0.14	341	565	537
4	4	2	9	0.091	771	1418	1350
5	5	2	4	0.091	651	1030	980
6	6	2	9	0.091	1112	1983	1887
7	7	3	14	0.074	7497	1771	1685
8	8	3	13	0.074	8772	1909	1991
9	9	3	13	0.074	7838	2336	2222
10	10	4	14	0.024	8268	3189	3035
11	11	4	14	0.024	2234	1474	10529
12	12	4	9	0.024	3005	2892	11879
13	13	5	10	0.005	17917	627	4479
14	14	5	10	0.005	18227	1092	4922
15	15	5	11	0.005	18258	1192	5016

general, the demand points are usually serviced by the nearest storage facilities. A total of 44 lateral transshipment activities occurred in 12 scenarios, as summarized in Table 6, and there is no lateral activity in scenarios #4, #13 and #14. In half of those 12 scenarios, all three commodity types are transshipped, and in the remaining scenarios, only one or two commodity types are transshipped. Moreover, there are only eight assignment relationships in the 44 lateral activities, i.e., (4, 8, 9), (8, 4, 2), (8, 4, 3), (10, 8, 4), (10, 8, 5), (11, 10, 9), (11, 12, 13) and (11, 12, 14). The three numbers in parentheses represent the original facility node, the transshipment facility node, and demand node in the lateral transshipment activities, respectively. It can be found that the facility-demand point assignments in the lateral transshipment activities are almost unchanged for different scenarios and commodities. For instance, all three commodities are transshipped from facility #4 to demand node #9 through facility #8 in both scenarios #10 and #15.

The overall objective function value for this solution is \$25,667,918, and the composition of the total cost is shown in Fig. 3. The largest part in the total cost is the commodity acquisition cost, which accounts for approximately 65%. Note that the sum of the penalty cost for unsatisfied demand and the holding cost for the surplus of commodities accounts for a quarter of the total cost, which is a direct result of the distribution of demand across scenarios. Specifically, a hurricane of category 1 has the highest occurrence probability, but the resulting demand for relief supplies is not very large. In contrast, the demand for relief supplies caused by a hurricane of category 5 is very large, but its occurrence probability is very low. The pre-positioned relief supplies are not sufficient to satisfy all the demand in the worst-case scenarios due to the low occurrence probability. The out-of-stock penalty cost is directly proportional to the gap between the actual demand and the pre-positioned stock level. If the pre-positioned stock can satisfy the highest demand, the out-of-stock penalty cost will be reduced to zero. However, in that situation, due to the very low occurrence probability of high demand, a high holding cost will be incurred with a high probability and the acquisition cost will increase accordingly. The developed model can find an optimal trade-off between the out-of-stock penalty cost and the holding cost.

4.3. Comparison with direct shipment model

To explore the effect of lateral transshipment on the solution, the direct shipment problem (P_0) was solved in the same computing environment as the lateral transshipment problem (P_1), and the parameters were assigned the same values as the corresponding values in Section 4.1. The direct shipment problem contains 15,330 constraints and 14,940 variables (including 1680 binary variables), which was solved in

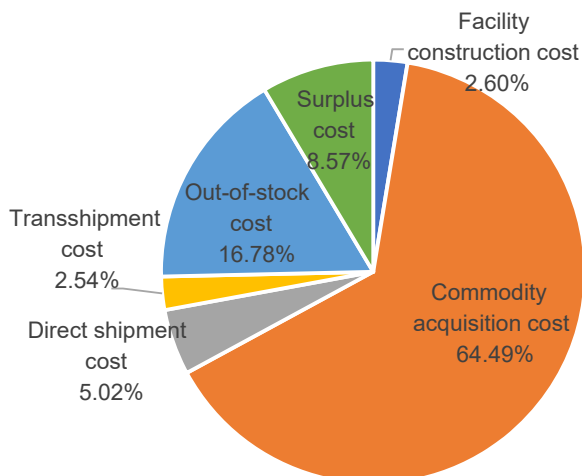


Fig. 3. The composition of the total cost for the baseline solution.

Table 7

Results of first-stage decision variables in the direct shipment problem.

Node	City	Facility size	Water (1000 gals)	Food (1000 meals)	Medicine	Space utilization rate
2	Corpus Christi	Small	5	7	7	3.61%
7	Beaumont	Medium	1162	1388	1419	69.9%
11	Tallahassee	Medium	1997	472	449	80.5%
12	Orlando	Large	4679	1106	1052	98.71%
Total =			7843	2973	2927	

about 19 s of CPU time. Table 7 presents the results of first-stage decision variables in the direct shipment problem.

The solution to the direct shipment problem has a total of four open facilities, and two of the facility locations are the same as in the lateral transshipment problem, but the mix of supplies pre-positioned is different. It is worth noting that the new opened facility #2 in Corpus Christi only stocks 5 units of water, 7 units of food and 7 units of medicine, and its space utilization rate is only 3.61%. The extremely low utilization rate of facility #2 shows that setting up a facility here is not a wise choice, but in order to meet the demands of the surrounding areas, a relief facility has to be set up here. Furthermore, this also reveals that the lateral transshipment option can make the pre-positioning and distribution of relief supplies more flexible.

The optimal objective function value for the direct shipment problem (P_0) is \$28,860,246, which is an increase of \$3,192,329 compared with the optimal total cost of the lateral transshipment case, indicating that the lateral transshipment plan is more cost-effective than the direct shipment plan. Table 8 compares each composition of the total costs for the direct shipment problem (P_0) and the lateral transshipment problem (P_1). Compared with the direct shipment problem, when the lateral transshipment is included, there is a decrease in the commodity acquisition cost, direct shipment cost and the hold cost for the surplus of relief supplies, which is partially offset by an increase in the facility construction cost, the lateral transshipment cost and the out-of-stock penalty cost. The greatest reduction is in the commodity acquisition cost, which decreases by \$3,841,800, indicating that fewer relief supplies are pre-positioned at storage facilities. Meanwhile, the decrease in the pre-positioned relief supplies leads to an increase in the penalty cost for unmet demand, and a decrease in the holding cost.

4.4. Sensitivity analysis

In this section, we conduct sensitivity analysis to study how the out-of-stock penalty cost and the maximum travel distance will affect the decisions on the pre-positioning and distribution of relief supplies. All the cases will be compared with the baseline results presented in Section 4.2.

4.4.1. The out-of-stock penalty cost

In the baseline case in Section 4.2, for each type of relief commodities, the out-of-stock penalty cost is assumed to be ten times its procurement price, which indicates that these three types of relief commodities are equally important. In practice, the importance of different goods may not be the same in most instances. Generally speaking, the drinking water and food are essential to daily life and should be given more attention. If there are injured people, medicines are most needed and should be put more emphasis. In this section, three instances as shown in Table 9 are designed to explore the impact of out-of-stock penalty cost on the optimal solution.

These three cases are solved in the same computing environment, and the results are summarized in Table 10, together with the baseline results for comparison. Note that the quantity of medicine pre-positioned in case C is more than five times that of the baseline case, while the amounts of water and food stay almost unchanged. The reason

Table 8The composition of the overall costs for P_0 and P_1 (in US dollars \$).

Problem	FC	AC	DC	TC	PC	HC	Total cost
P_0	696,400	21,603,400	195,186	0	3,052,380	3,312,880	28,860,246
P_1	716,000	17,761,600	138,114	69,893	4,620,800	2,361,510	25,667,917
Difference	19,600	-3,841,800	-57,072	69,893	1,568,420	-951,370	-3,192,329

* FC represents the facility construction cost; AC represents the commodity acquisition cost; DC represents the direct shipment cost; TC represents the lateral transshipment cost; PC represents the out-of-stock penalty cost; HC represents the holding cost for the surplus of supplies.

Table 9

Case description and setting.

Name	Setting
Case A	PC^1 is increased to 100 times AC^1 , while PC^2 and PC^3 are kept at 10 times AC^2 and AC^3 , respectively;
Case B	PC^2 is increased to 100 times AC^2 , while PC^1 and PC^3 are kept at 10 times AC^1 and AC^3 , respectively;
Case C	PC^3 is increased to 100 times AC^3 , while PC^2 and PC^1 are kept at 10 times AC^2 and AC^1 , respectively.

* PC^k ($k = 1, 2, 3$) denote the unit penalty cost for the shortage of water, food and medicine, respectively; AC^k ($k = 1, 2, 3$) represent the unit procurement cost for water, food and medicine, respectively.

Table 10

Case results.

	Baseline case	Case A	Case B	Case C
Quantity of relief supplies pre-positioned				
Water (1000 gals)	7839	11,534	7842	6479
Food (1000 meals)	2283	2966	3189	2334
Medicine	2222	2937	2926	11,870
Number of facilities	5	4	4	4
Small-size	2	1	1	1
Medium-size	2	1	2	2
Large-size	1	2	1	1
Total cost (\$)	25,667,918	38,092,668	29,441,720	28,797,928
Construction cost (\$)	716,000	808,000	696,400	696,400
Acquisition cost (\$)	17,761,600	23,957,000	22,773,300	18,511,300
Direct shipment cost (\$)	138,114	147,915	104,744	134,237
Lateral transshipment cost (\$)	69,893	74,853	53,006	67,931
Out-of-stock cost (\$)	4,620,800	9,394,810	2,230,010	6,789,820
Holding cost (\$)	2,361,510	3,710,090	3,584,260	2,598,240

behind this phenomenon is that the relief commodity with a higher out-of-stock penalty cost is more emergent, and the demand for it should be satisfied first. Once such relief supplies are out of stock, a very high penalty cost will be incurred. Therefore, it is safe to draw a conclusion that the higher the out-of-stock cost of a relief commodity (namely the greater importance of this item), would lead to that more such relief supplies are pre-positioned.

Furthermore, compared with the baseline case, one more large-size facility is opened in case A, which results an increase in the facility construction cost by \$92,000. While one small-size facility is closed in case B and case C. These results are attributed to the intrinsic feature of relief supplies. As can be seen from the second column of Table 2, water is the most space-consuming and medicine is the least space-consuming. Therefore, when an approximate amount of increased relief supplies is pre-positioned, the occupied space to stock water is much larger than medicine. In addition, the total costs of all three cases increase dramatically compared with the baseline case, especially in case A. The increase in the total cost is mainly attributed to the huge increase in the commodity acquisition cost, which indicates more relief supplies are

pre-positioned.

4.4.2. The maximum travel distance

In the baseline case, the maximum travel distance is assumed to be 500 miles. The time spent on the road is positively related to the distance traveled. Due to the emergency of disasters, the relief supplies usually need to be delivered to demand points as soon as possible. The requirement for the time spent on the road limits the maximum travel distance. To explore the impact of the maximum travel distance on the solution, several experiments are conducted where the maximum travel distances ranging from 100 miles to 900 miles while the other parameter values stay the same as in Section 4.1. The results are depicted in Fig. 4.

From Fig. 4, it is obvious that the commodity acquisition cost and out-of-stock penalty cost account for the vast majority of the overall costs, regardless of the maximum travel distances. Moreover, it also can be found that the overall costs and the number of open facilities decrease with the increase in the maximum travel distances. To be more specific, when the maximum travel distances range from 100 to 300 miles, the overall costs decrease steadily from \$49.1 million to \$29.8 million; when the maximum travel distances range from 300 to 900 miles, the overall costs decrease slightly from \$29.8 million to \$25.5 million.

To further explore the reasons behind this, we found that when the maximum travel distance is short enough, the affected area covered by a storage facility is also very small. Thus it needs to build more facilities to satisfy the demands as much as possible, otherwise, it will incur more penalty cost. Meanwhile, the majority of the opened storage facilities are small-sized and the space utilization rate is very low when the maximum travel distance is short enough. For instance, when the maximum travel distance is 100 miles, the storage facility at node #5 only stocks 1 unit of water, 1 unit of food and 1 unit of medicine. In the extreme situation where the maximum travel distance is less than the distance between any two nodes, the storage facility at any node can only meet its own demand and cannot provide any relief supply to any other node, and there is no lateral transshipment activity in this instance. Thus it needs to find an optimal tradeoff between the facility construction cost and the out-of-stock penalty cost. With the increase in the maximum travel distance, the scope covered by a storage facility also increases and the number of open supply facilities decreases accordingly. Meanwhile, some small-sized facilities are expanded and more relief supplies are pre-positioned, which leads to a decrease in the out-of-stock penalty cost. Although the decrease in the out-of-stock penalty cost is partially offset by the increase in the commodity acquisition cost, the overall cost still decreases. When the maximum travel distance is long enough, the scope covered by a storage facility is also very large accordingly. In the meanwhile, the travel time will become very long when relief supplies travel a long distance. However, the demand for the relief is very urgent in reality, and the maximum travel time is limited. Therefore, the overall cost stays stable when the maximum travel distance is long enough.

From the above analysis, we can conclude that the solution with a greater value of R is more flexible. When R is small enough, in order to satisfy the demand in the affected area, the only strategy is to build a large number of storage facilities, which results in a very low space utilization rate for many facilities. With the increase in the maximum travel distance, a storage facility can serve more demand nodes and the decision-makers have more options to cope with the hurricanes. For example, those small-size facilities with low space utilization rate can be

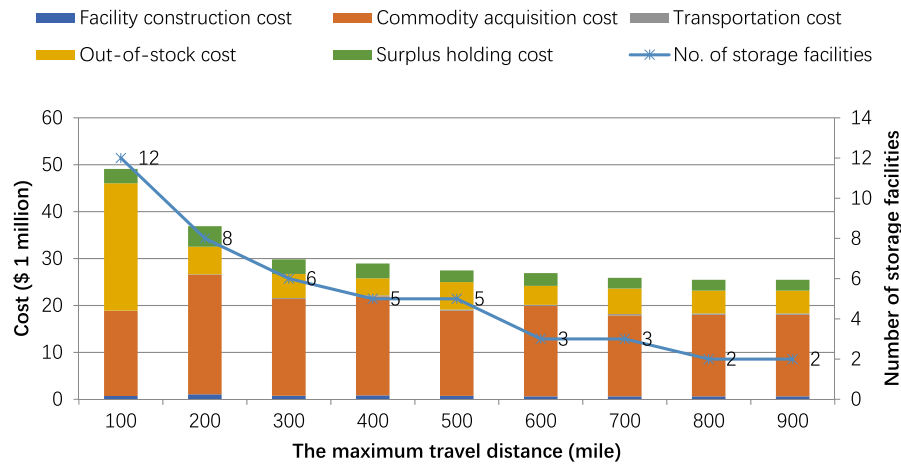


Fig. 4. Sensitivity analysis results for the maximum travel distance.

integrated into large-size facilities. However, it is not wise to endlessly increase the value of R due to the emergency nature of disaster relief. As can be seen in Fig. 4, when R exceeds 300 miles, there is little change in the overall cost. In practice, the decision-makers need to seek a balance between the time limit for humanitarian relief and the overall cost.

5. Conclusions

In this study, lateral transshipment is included in humanitarian relief logistics. A two-stage stochastic programming model is formulated to address the joint decision-making of pre-positioning and distribution of relief supplies under uncertain environment. These uncertainties include the occurrence probability, landfall nodes, the damage degree of hurricanes, as well as the corresponding demand for relief supplies, and all these uncertainties are defined in a set of scenarios. The developed model minimizes the overall cost (including the facility construction cost, commodity acquisition cost, transportation cost, holding cost and out-of-stock penalty cost) and considers the uncertainties of disasters.

A case study addressing hurricane threats in the Gulf of Mexico region of the southeastern United States is conducted to illustrate the developed two-stage stochastic programming model. By comparison with direct shipment solution, the lateral transshipment solution is demonstrated to be more cost-effective and flexible. The sensitivity analysis of out-of-stock penalty cost and maximum travel distance also has provided some managerial insights for relief agencies. First, if a type of relief supply is urgently needed, it can be assigned a higher stockout penalty cost, which will result in an increase in its pre-stock to guarantee timely delivery of this commodity. Second, the solution with greater maximum travel distance is more cost-effective and flexible, but it also should be subject to the time limit for humanitarian relief.

There are two major directions for future research. First, more practical factors should be taken into account to extend the developed model. For instance, the priority of demand points should be considered. In practice, the situation in some demand points is more urgent and should be served first [27]. Furthermore, the priority of demand points may change dynamically with the progress of the rescue work. In addition, the assumption that each storage facility is allowed to use at most one other facility for lateral transshipment can be relaxed in our future work. Second, this study conducts a case study with 15 nodes in 15 scenarios, and it is efficient to solve those experiments using commercial solvers. However, real-world problems are usually more complicated and as the scale of the problem grows, it is computationally expensive to solve the developed model. Therefore, developing an efficient algorithm for large-scale problems will be another major effort in our future work, and possible algorithms include 2-step solution,

L -shaped, progressive hedging and sample approximation algorithm [28].

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CRediT authorship contribution statement

Yusheng Wang: Visualization, Methodology, Writing - original draft, Funding acquisition. **Zhijie Sasha Dong:** Conceptualization, Methodology, Supervision, Writing - review & editing, Funding acquisition. **Shaolong Hu:** Data curation, Validation.

Declaration of competing interest

Declarations of interest: none.

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Dr. Yusheng Wang: was born in Fuyang, Anhui Province, China in 1990. He received his B. S. degree in logistics engineering from Anhui University of Technology, Maanshan, Anhui Province, in 2012, and his PhD degree in management science and engineering from Sichuan University, Chengdu, Sichuan Province, in 2017. Since 2017, he has been an assistant professor at the School of Management Science and Engineering, Nanjing University of Information Science & Technology. His research interests include disaster management, system reliability improvement, transportation system optimization.

Dr. Zhijie (Sasha) Dong: is currently an Assistant Professor of Industrial Engineering at Texas State University. She received her B.S. degree in Architectural Engineering at Nanjing University in 2011, M.S. degree in Civil Engineering at Columbia University in 2012, and Ph.D. degree in Civil Engineering at Cornell University in 2015. Dr. Dong's primary research interest is the development of mathematical models and solution methods for use in the management of complex systems. Her current research focuses include disaster response, emergency management, and logistics and supply chain.

Dr. Shaolong Hu: received his Ph.D. degree in Management Science and Management at Tongji University in 2017. He is now working at Southwest Jiaotong University as an assistant professor. His research interests are in intelligent algorithm and engineering optimization in transportation, logistics and emergency management. He has published several papers on high-ranking peer-reviewed journals (e.g. *Transportation Research Part B: Methodological*, *Omega*, *Transportation Research Part E: Logistics and Transportation Review*) about disaster response and discovery.