A study of stochastic optimization problem for humanitarian supply chain management

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Abstract

Due to the frequency increase of natural disasters such as the earthquake and tsunami, the humanitarian supply chain management (SCM) became an important topic for scientific research. This paper proposes a two-stage stochastic model to optimize the cost of the whole relief process under uncertainty about demand, pre-positioned stocks and the condition of the transportation network. Many factors are considered such as fleet size, route availability and the extra stocking amount. The model also requires that in each scenario the satisfied proportion should be at least meet the lowest satisfaction value, which is decided by the properties of each area and the event. A case study application is used to illustrate the model and how it supports an emergency relief strategy.

Keywords : Humanitarian SCM, Stock estimation, Scenario analysis, Stochastic optimization problem, TOPSIS method

1. Introduction

Humanitarian supply chain management is the creation through which communities reduce vulnerability to hazards and cope with disasters. The events covered by disaster management include acts of terrorism, industrial sabotage, fire, natural disasters such as earthquakes and hurricanes, public disorder, industrial accidents, and communication failures. As an advanced humanitarian time series scheduling problem (Fig. 1), Duran (2012) mentioned that the disaster management is comprised of four sequential stages occurring during the life cycle of the disaster— Mitigation, Preparedness, Response and Recovery. During the mitigation stage actions are taken to prevent the onset of the disaster or moderate its effects. The preparedness stage aims at decreasing the response time by purchasing the relief commodities in advance and pre-positioning of needed supplies. In the response stage, the disaster mitigations plans are activated and the emergency supplies are distributed. The last step is the recovery stage, which includes retrieving the victims, rebuilding the infrastructure, and mitigating damages in the disaster areas.

Application of operations research in disaster logistics management has been one of the main issues in recent decades. Supply chain and logistics management are recently being used as analytical tools and techniques to provide efficient and effective relief to people who need help in devastated areas with optimized functions and activities. According to Carmen and Mark (2012), pre-positioning provides numerous benefits to relief organizations. First, relief commodities stored in the distribution center reduce the response time assisting disaster victims. Second, through the advanced procurement of supplies humanitarian organizations can consider local, regional and international suppliers, so they can get better prices for the relief commodities. Thirdly, by buying in larger volumes humanitarian organizations can increase their purchasing power and take advantage of lower bulk prices. The aim of response to disasters in humanitarian relief chains is to provide quick relief to affected areas in order to minimize the death and pain of people. In this paper, we focus on the preparedness and response stages, specifically the pre-positioning of the relief commodities and dispatching the relief commodities during the progression of the event.

Fig. 1 An advanced humanitarian time series scheduling

However, according to Goncalves (2011), many humanitarian decision makers often make decisions by over-reliance on the past experiences. Failure to create a plan could lead to human mortality, lost revenue, and damage to assets. This motivates this paper to study the stochastic models that can deal with the urgent complexity and uncertainty to help these decision makers. Due to the increased frequency and severity of disasters around the world in recent decades, the disaster management field have been the subject of growing public concern and research interest. (Smith, et al., 2009)

Several researchers have addressed problems of post-event distribution of emergency supplies. Important examples include the work of Haghani and Oh (1996), Sheu and Hsu (1997), Houming et al.,(2008) and Yan and Shi (2009). These models assume that the characteristics of the event, the resulting demands for the supplies, the locations and the available quantities of those supplies, and the condition of the transportation network are known. Haghani and Oh (1996) develop a multi-commodity, multi-mode network flow model to help emergency response managers organize detailed load plans for dispatching the relief commodities after a disaster.

Recently, two-stage stochastic models have been successfully used in humanitarian logistics and disaster management as they allow the modeler to represent pre-event and post-event phases together via the two stages decision variables. Barbarosoglu and Arda (2004) firstly develop a two-stage stochastic model for both pre-event and post-event stages in disaster response, considering the uncertainties in available supplies and demands by generating a set of scenarios. Related work has been done by Ozdamar et al. (2004), who created a dynamic model to generate multi-period vehicle routes and schedules along with commodity assignments.

The above papers do not consider route or link probability in their transportation plans. Route probability, which relates to road conditions, represents one of the uncertainty factors that occur after a disaster strikes. Therefore, it is very important to consider route probability into the model. Opit and Nakade (2016) generate all possible path combinations, which is also the scenarios that we use in this paper. A mixed-integer programming model which limited by the route condition and budget is developed to maximize the amount of relief supplies sent to disaster areas.

In this study, rather than just focus on routing problem, we also want to make a proper plan both for the Preparedness phase (Stocking Estimation) and the Response Phase (Dispatching Plan). At the same time, many factors should be taken into consideration such as the available amount of relief commodities, available vehicle's numbers, or even how to reduce the regional satisfied differences and so on.

2. A two-stage stochastic model for disaster management

A two-stage model is formulated which combines decision on stocking levels for emergency supplies with the distribution of those supplies to multiple demand locations after an event, with uncertainty about demand, survival of pre-positioned stocks and the condition of the transportation network after the disaster. The whole structure of this 2-stage model can be demonstrated in Fig.2.

In pre-disaster period (stage 1), we want to estimate the stocking amount which limits by the demand of each disaster area, the route condition, capacity of the distribution center. In the post-disaster period (stage 2), in order to get a detailed dispatching plan, we minimize the total cost by the limited stocking relief amounts, route conditions, vehicles numbers, demands and the lowest satisfied degree.

2.1 Assumptions of the model

- I. The uncertainty of demands from all disaster areas is reflected by probabilistic scenarios, and the demand information under each scenario is supposed accurately.
- II. It is assumed that the distribution centers' number and location, vehicles' type and number are decided by the local authorities.
- III. As the number of vehicles is limited, the relief demands from all the affected areas cannot be guaranteed to be satisfied completely in the allocation process.
- IV. In making transportation plan for vehicles, each vehicle is required to return to its departure position after

Fig. 2 Structure of the disaster logistics management mode

finishing its current mission.

V. It is supposed that helicopters can serve all of the disaster areas.

2.2 Notations of the model

The full mathematical model uses the following notations.

Indices and sets

A : the set of commodities

I : the set of distribution centers

J : the set of disaster areas

M : the set of vehicle types

S : the set of scenarios

$f_1(s)$: The set of sub-scenarios during time period 1

T : the set of time periods

Parameters

CAP_i : Capacity of distribution center i , $i \in I$

PC_a : A unit procurement cost of commodity a , $a \in A$

w_a : Unit weight of commodity type a , $a \in A$

c_a : Unit volume of commodity type a , $a \in A$

γ_a : Degree of importance of commodity type a , $a \in A$

($0 < \gamma_a < 1$; $\sum_a \gamma_a = 1$)

π_a : Penalty coefficient of unsatisfied demand typed a

α_{aj} : The lowest satisfied degree of commodity type a in disaster area j , $a \in A, j \in J$

vw^m : Weight capacity of vehicle m , $m \in M$

vc^m : Volume capacity of vehicle m , $m \in M$

v^m : The average velocity of vehicle m , $m \in M$

TC_m : The transportation cost per kilometer of vehicle m

QC_m : The cost to rent a vehicle of type m in the post-disaster period

NV_{im} : Available number of vehicles of type m for distribution center i

N_{im} : Maximum available transportation times of using NV_{im} vehicles of type m for each distribution center i

L_{ij} : The distance from distribution center i to disaster area j , $i \in I, j \in J$

P_s : Probability of scenario s , $s \in S$

D_{aj}^s : Amount of demanded commodity type a at disaster area j in scenario s , $s \in S$, $j \in J$

$R_{ijmt}^s = \begin{cases} 1, & j \text{ is reachable from } i \text{ by } m \text{ at } t \text{ in } s \\ 0, & \text{otherwise} \end{cases}$

$i \in I, j \in J, s \in S, m \in M, t \in T$

$Z_{ij}^m = \begin{cases} 1, & j \text{ is reachable from } i \text{ by } m \text{ at } t \text{ in } s \\ 0, & \text{otherwise} \end{cases}$

$i \in I, j \in J, s \in S, m \in M, t \in T$

M : A very large positive number

β : Extra stocking coefficient

η : The unit penalty coefficient

δ : The maximum of response time limit from distribution center to disaster area

Decision variables in stage 1

X_{aijmt}^s : The amount of commodity type a dispatched from distribution center i to disaster area j by vehicle m at period t in scenario s

UD_{ajt}^s : Amount of unsatisfied demand of commodity type a at disaster area j at time t in scenario s

$STOC_{ai}^s$: The stocking amount of commodity typed a in distribution center i

N_{ijmt}^s : Number of vehicle m moved from distribution i to disaster area j at period t in scenario s

Added variables in stage 2

QV_m^s : Additional vehicle numbers of type m in scenario s

Q_{im}^s : Available transportation times for QV_{im}^s vehicles

2.3. Stage 1 – stocking forecast

In stage 1, we are going to estimate the stocking amount which limits by the demand of each disaster area, the route condition, capacity of the distribution center and the lowest satisfied degree of each disaster area.

In this model, the objective is to minimize the total cost under the constraint to satisfy the victims. So in this stage, we add an extra stocking coefficient β , which is used as adjusting the stocking level. β is also an important factor to link stage 1 and stage 2.

2.3.1. Scenarios generation for stage 1

To take uncertainty into account, we propose a set of scenarios based on the route availability, which is shown in Table 1. In the relief process, some disrupted roadway may be repaired in the next time period.

Table 1 shows the scenarios generation of 2 time periods. We suppose that the number of the routes is n , number of disrupted routes in 1st time period is k , number of repaired routes is l .

In the 1st time period, the probability of each route to be disrupted is q_1 ; in the 2nd time period the probability of each disrupted route to be repaired is q_2 . Therefore, the probability of routes being available for each scenario s (denoted by P_s) is calculated as follows:

$$\begin{aligned} P_1(s_1) &= q_1^k \cdot (1 - q_1)^{n-k}; \\ P_2(s | s_1) &= q_2^l \cdot (1 - q_2)^{k-l}; \\ P_s &= P_1(s_1) \cdot P_2(s | s_1), \text{ where, } s_1 = f^1(s) \text{ and } s \in S. \end{aligned}$$

Each $s_1 \in S$ means the route condition in time period 1, and S is the set of the scenarios during the whole dispatching process. To understand the generation of the scenarios clearly, here is a sample in Table 1.

In Table 1, a binary code represents the availability of each route at one point in time, where 0 means the route is unavailable and 1 means the route is available. It is assumed that every available route during period 1 remains available during period 2. For instance, the route condition of the scenario 67 (s_{67}) was changed from period 1 to period 2 as $(0,0,0,0,0,1) \rightarrow (0,0,0,1,0,1)$, which means that the fourth route disrupted in period 1 is available in period 2, whereas the first, second, third and fifth routes are disrupted in both periods 1 and 2.

In this case study, the number of routes is $n=6$. The possible scenario for period 1 can be formulated as the combination of routes available (Number of scenarios in period 1 is $2^6 = 64$.) The number of possible scenarios in period 2 can be calculated by

$$\sum_{k=0}^n \sum_{l=0}^k \binom{n}{k} \times \binom{k}{l} = \sum_{k=0}^n \binom{n}{k} 2^k = 3^n = 3^6 = 729.$$

Table 1 Sample of scenarios generation

s_1 (Scenarios in t1)	Route availability in t1 (f_1^s)	Route availability in t2	s
1	(0,0,0,0,0,0)	(0,0,0,0,0,0)	s1
		(0,0,0,0,0,1)	s2
		(0,0,0,0,1,0)	s3
		...	...
2	(0,0,0,0,0,1)	(1,1,1,1,1,1)	s64
		(0,0,0,0,0,1)	s65
		(0,0,0,0,1,1)	s66
		(0,0,0,1,0,1)	s67
...	...	...	...
		(1,1,1,1,1,1)	s96
64	(1,1,1,1,1,1)	(1,1,1,1,1,1)	s729

2.3.2 Model formulation of stage 1

The 1st stage's model for estimate the stocks is formulated as follows:

$$\text{Min} \quad f1 = \sum_a \sum_i PC_a \cdot STOC_{ai} \quad (1)$$

s.t.:

Commodity flow constraints

$$X_{aijmt}^s \leq MR_{ijmt}^s Z_{ij}^m$$

$$\forall a \in A; i \in I; j \in J; m \in M; s \in S; t \in T; \quad (2)$$

$$\sum_i \sum_m (X_{aijm1}^{f_1(s)} + X_{aijm2}^s) \leq D_{aj}^s$$

$$\forall a \in A; j \in J; f_1(s) \in S_1; s \in S; \quad (3)$$

$$D_{aj}^s - \sum_i \sum_m X_{aijm1}^{f_1(s)} = UD_{aj1}^{f_1(s)}$$

$$\forall a \in A; j \in J; f_1(s) \in S_1; s \in S; \quad (4)$$

$$UD_{aj1}^{f_1(s)} - \sum_i \sum_m X_{aijm2}^s = UD_{aj2}^s$$

$$\forall a \in A; j \in J; f_1(s) \in S_1; s \in S; \quad (5)$$

Facility capacity and numbers

$$\sum_j \sum_m X_{aijm1}^{f_1(s)} + \sum_j \sum_m X_{aijm2}^s \leq STOC_{ai}$$

$$\forall a \in A; i \in I; f_1(s) \in S_1; s \in S; \quad (6)$$

$$\sum_a STOC_{ai} c_a \leq CAP_i$$

$$\forall i \in I \quad (7)$$

Vehicle capacity and numbers

$$N_{ijmt}^s \leq MR_{ijmt}^s Z_{ij}^m$$

$$\forall i \in I; j \in J; t \in T; m \in M; s \in S; \quad (8)$$

$$\sum_a X_{aijmt}^s \cdot c_a \leq N_{ijmt}^s \cdot VC^m$$

$$\forall i \in I; t \in T; m \in M; j \in J; s \in S; \quad (9)$$

$$\sum_a X_{aijmt}^s \cdot w_a \leq N_{ijmt}^s \cdot VW^m$$

$$\forall i \in I; m \in M; j \in J; s \in S; \quad (10)$$

Lowest stocking amount constraints

$$\frac{\sum_m \sum_i (X_{aijm1}^{f_1(s)} + X_{aijm2}^s)}{D_{aj}^s} \geq \beta \cdot \alpha_{aj}$$

$$\forall a \in A; j \in J; f_1(s) \in S_1; s \in S; \quad (11)$$

Non-negativity and integrality

$$X_{aijmt}^s \geq 0$$

$$\text{Real number.} \quad (12)$$

$$STOC_{ai} \geq 0$$

$$\text{Real number.} \quad (13)$$

$$N_{ijmt}^s \geq 0$$

$$\text{Integer.} \quad (14)$$

In the 1st stage, the objective function (1) is the sum of the procurement cost to be minimized. Constraint (2) means that the transportation happens only when the route is available and the post-time is smaller than the limited

response time δ . Constraint (3) gives the upper-bound on a transported amount of each commodity. Constraint (4) shows the relationship among the demand, satisfied demand and the unsatisfied demand of each time period. Constraint (5) means the total amount of transported commodities should be less than or equal to the stocking amount. Constraint (6) limits the stocking amount by the capacity of the distribution center. Constraint (7) means the vehicle is usable only when the route is available and the post-time is smaller than the limited response time δ . Constraint (8) limits the effective transport-times by vehicle numbers which is prepared previously and additionally. Constraint (9)~(10) limits the transported commodities by the loading capacity and volume of each vehicle. Constraint (11) is the lowest satisfaction proportion of each disaster area and each commodity. (In constraint (11), when $\beta * \alpha_{aj} > 1$, then make $\beta = 1 / \alpha_{aj}$) Constraint (12), (13), (14) means that the stocking amount, transported amount should be positive; transporting time should be a positive integer.

Through the 1st stage we can forecast the stocking amount of each commodity which is the most appropriately under each scenario. Our objective function is going to make the stocking cost as small as possible.

2.4. Stage 2 – delivering planning

In stage 2, we want to know the best dispatching route and allocation plan of the post-disaster period. As the government can grasp the route condition just after the disaster occurs, $f_1(s)$ can be decided shortly at the beginning of this period. So we can use this route condition to estimate the route condition later. In stage 2, the objective is to minimize the total cost including the transportation cost, the vehicles rental cost, the fuel cost and the penalty cost of the unsatisfied demands. Here the penalty cost is used to raise the average satisfied proportion. Therefore, we can find an appropriate plan to dispatch these stocking commodities.

When disaster happens, a number of vehicles are needed to dispatch the relief commodities. However, it is a difficult thing to rent such large number of vehicles in a short time. Here we supposed that only a few number of vehicles can be rent at the ordinary rental price. Rest of vehicles can be added but at a higher price than before.

Meanwhile, in order to use the vehicles fully, one vehicle can travel several times between the distribution center and disaster area. The available travel times of each vehicle Q_{im}^s are limited by the number of available vehicles QV_m^s , travel distance L_{ij} , the length of each time period δ and the average speed of each vehicle's type. Each type of vehicle has a maximum additional number Max_m . These can also be presented by the equations below:

$$Q_{im}^s = QV_m^s \cdot [\delta / (\max(L_{ij} / v^m))] \quad (15)$$

where $QV_m^s \leq Max_m$.

2.4.1. Scenario generation for stage 2

In the post-disaster phase, the route condition just after the disaster $f_1(s)$ was known already. Therefore,

$$P_s = P(s_1) \cdot P(s | s_1) = P(s | s_1)$$

2.4.2. Model formulation of stage 2

The 2nd stage's model for delivering planning is formulated as follows:

$$\text{Min} \quad f2 = \sum_s p_s [\sum_m \sum_i \sum_j ((N_{ijm1}^{f_1(s)} + N_{ijm2}^s) \cdot TC_m \cdot L_{ij} + QC_m \cdot QV_m^s) + \sum_j \sum_a UD_{aj2}^s \cdot \pi_a] \quad (16)$$

Commodity flow constraints

s.t.

$$X_{aijmt}^s \leq MR_{ijmt}^s Z_{ij}^m \quad \forall a \in A; i \in I; j \in J; m \in M; \quad t = 1, s = f_1(s); t = 2, s \in S; \quad (17)$$

$$\sum_i \sum_m (X_{aijm1}^{f_1(s)} + X_{aijm2}^s) \leq D_{aj}^s \quad \forall a \in A; j \in J; s \in S; \quad (18)$$

$$D_{aj}^s - \sum_i \sum_m X_{aijm1}^{f_1(s)} = UD_{aj1}^{f_1(s)} \quad \forall a \in A; j \in J; s \in S; \quad (19)$$

$$UD_{aj1}^{f_1(s)} - \sum_i \sum_m X_{aijm2}^s = UD_{aj2}^s \quad \forall a \in A; j \in J; s \in S; \quad (20)$$

Facility capacity and numbers

$$\sum_j \sum_m X_{aijm1}^{f_1(s)} + \sum_j \sum_m X_{aijm2}^s \leq STOC_{ai} \quad \forall a \in A; i \in I; s \in S; \quad (21)$$

Vehicle capacity and numbers

$$N_{ijmt}^s \leq MR_{ijmt}^s Z_{ij}^m \quad \forall i \in I; j \in J; m \in M; \quad t = 1, s = f_1(s); t = 2, s \in S; \quad (22)$$

$$\sum_i \sum_j N_{ijmt}^s \leq N_{im} + Q_{im}^s \quad \forall i \in I; t \in T; m \in M; s \in S; \quad (23)$$

$$Q_{im}^s = QV_m^s \cdot [\delta / (\max(L_{ij} / v^m))] \quad \forall i \in I; j \in J; t \in T; m \in M; s \in S; \quad (24)$$

$$QV_m^s \leq Max_m \quad \forall m \in M; s \in S; \quad (25)$$

$$\sum_a X_{aijmt}^s \cdot c_a \leq N_{ijmt}^s \cdot VC^m \quad \forall i \in I; m \in M; j \in J; t \in T; s \in S; \quad (26)$$

$$\sum_a X_{aijmt}^s \cdot w_a \leq N_{ijmt}^s \cdot VW^m \quad \forall i \in I; m \in M; j \in J; t \in T; s \in S; \quad (27)$$

Lowest satisfaction proportion constraints

$$\frac{X_{aijm1}^{f1(s)}}{D_{aj}^s} \geq \varphi \cdot \alpha_{aj} \quad \forall a \in A; j \in J; s \in S; \varphi < 1 \quad (28)$$

$$\frac{\sum_m \sum_i (X_{aijm1}^{f1(s)} + X_{aijm2}^s)}{D_{aj}^s} \geq \alpha_{aj} \quad \forall a \in A; j \in J; s \in S; \quad (29)$$

Unit penalty cost

$$\pi_a = \eta \cdot \gamma_a \cdot PC_a \quad \forall a \in A; \quad (30)$$

Non-negativity and integrality

$$X_{aijmt}^s \geq 0 \quad \text{Real number; (31)}$$

$$N_{ijmt}^s, QV_{im}^s \geq 0 \quad \text{Integer. (32)}$$

In the 2nd stage, the objective function f2 minimizes the sum of rental cost for hiring vehicles, the fuel cost for vehicles and the penalty cost for unsatisfied demand. New constraints are added. Constraint (23) limits the available transporting times by the available number of each vehicles. Constraint (24) shows the relationship between the available transporting times of each vehicle type and available vehicle's number. Constraint (25) means that the additional vehicle's number is limited by its upper bound. Constraints (28) is the lowest satisfaction proportion constraint for the first time period, which limits the satisfied proportion in the 1st time period with the lowest bound value of $\varphi \cdot \alpha_{aj}$. Constraint (29) is the lowest satisfaction proportion constraints for the whole delivering process. Equation (30) shows the unit penalty cost can be adjusted by the value of η . Other constraints are the same meaning with constraints in stage 1. From stage 2, the proper dispatching plan for post-disaster period can be decided.

3. Case study

3.1 Test case description

In this section, we take the case constructed of the Si-chuan Province in China, which is located at the Earth-quake-prone zone. 6 disaster areas are identified from the most seriously affective areas and choose 1 city as the distribution center. The map of Relief Distribution Center (RDC) and Disaster Areas (DAs) is showed in Fig. 3 (Each DA is represented by alphabet from 'A' to 'F'). In this case study, 4 types of relief commodities are considered— Food, Water, Tent and Medicine. Table 2 shows the properties of each commodity. In the rescue period, 2 types of vehicles are used — helicopter and truck, and the features of each vehicle type shows in Table 3.

Fig. 3 Map of disaster areas and distribution center

Table 2 Features of each commodity

	Unit price (\$)	Unit weight (kg)	Unit volume (m ³)	Serving number (people)
Food(box)	12	4	0.054	5
Water(tank)	4.5	18	0.054	3
Tent(unit)	90	40	0.2	15
Medicine(box)	47	5	0.1887	10

Table 3 Features of each vehicle type

Vehicle type	Transport cost (\$/km)	Weight capacity (kg)	Volume capacity (m ³)	Velocity (km/h)	Rental cost (\$/24h)
Heli.	2.61	4100	45	252	28800
Truck	0.003	14000	1240	80	900

3.2. Determination of the lowest satisfied proportion

For each disaster area, there are various factors can affect the impact of the earthquake. There are several main factors which are distance from epicenter, population density, age of the residents, urbanization rate, density of buildings, geology, education and planning. In this study, we are going to evaluate the 6 disaster areas' rescue degree by focusing on these 4 factors: the population density, dependent ratio of aged population, distance from the epicenter and the urbanization rate of the six disaster areas.

Then we calculate the rescue degree of 6 disaster areas by the TOPSIS method. The procedure can be summarized as:

- Step 1. Create an evaluation matrix consisting of 6 alternatives and 4 criteria
- Step 2. Normalization of the evaluation matrix
- Step 3. Calculate the weighted normalized decision matrix
- Step 4. Determine the worst and the best alternative value
- Step 5. Calculate the distance between the target alternative and the worst condition.
- Step 6. Calculate the similarity to the worst condition
- Step 7. Rank the alternatives according to step 6.
- Step 8. Then we can get the lowest satisfaction degree by the equation .

4. Numerical results

In this case study, first we code each scenario explained in section 2.3.1 on Python 2.7.6. The solving time is less than 2 minutes. The 2-stage mathematical model presented in section 2 is realized on GAMS 24.1.3 and run by CPLEX12.5.1.0 solver on an Intel® Core™ i7-3770 Dual Processor with 24 GB RAM and 3.40 GHz CPU. The computation time of each test problem is less than 1 minute.

4.1 Result of stocking estimation

At first, we run the model of stage 1 demonstrated in section 2.3.2 under capacity of each distribution center of 14000 m³; maximum response time of 6 hours; lowest proportion of satisfied stated in section 3.2; extra stocking coefficient of 1, 1.5, 2, 2.5, 3, and 3.1 for commodity typed 1 to 4. The result of how does extra stocking coefficient affects the stocking amount is showed in Table 4.

Table 4 Stocking amount of each relief commodity (unit)

β	a1	a2	a3	a4
1.0	54990	67335	5985	5050
1.5	75729	99875	8978	7575
2.0	84233	114815	11970	10100
2.5	86902	123094	14055	12625
3.0	87374	124243	15308	14981
3.1	INFEASIBLE			

From Table 4 we can see that with the increasing of β , the stocking amount of each commodity is increasing. We can also know that the model turns to be infeasible when β is 3.1. When β becomes larger than 3.1, constraint (6) and (11) conflicts each other. In other words, the volume of all the relief commodities exceeds the distribution center's capacity.

4.2. Delivering plans with different extra stocking coefficient

Next, model of stage 2 which demonstrated in section 2.4.1 is run under stocking amounts showed in Table 5; the unit penalty cost of 37.80, 12.15, 162.00, 63.45 for commodities 1 to 4; the fuel costs of helicopter and truck are 2.61\$/km, 0.00295\$/km; the rental costs of helicopter and truck are 28800\$/day, 900\$/day,

With different value of β , not only the procurement cost in stage 1 changes, but also costs in stage 2 are changing as well. To illustrate this clearly, here is an example. When $f_1(s) = (1, 0, 1, 1, 0, 0)$, each part of the total cost is shown in Table 5.

To see the relationship between stage 1 and stage 2 clearly, Fig. 3 shows the average satisfied proportion of each disaster area when the Stocking extra coefficient β changes from 1 to 3 in scenario 636 (which route condition is $(1, 0, 1, 1, 0, 0) \rightarrow (1, 0, 1, 1, 0, 1)$). With the increasing of β , most disaster areas are served more relief commodities.

Fig. 3 Average satisfied proportion of each disaster with Different value of β

Table 5 Costs variation with different β

	Stage 1	Stage 2			Stage 1 & 2
β	Procurement cost (\$)	Rental cost (\$)	Trans. cost (\$)	Penalty Cost (\$)	Total Costs (\$)
1.0	1738935	400400	32869	4669300	6841504
1.5	2522261	435614	43354	2844952	5846181
2.0	3079562	452552	44513	1696941	5273568
2.5	3455142	456629	44968	1003947	4960686
3.0	3689502	457765	45071	629877	4822215

4.3. Delivering plans in different scenarios

In stage 2, to learn how does scenario effects the whole relief planning, we selected 3 different route conditions of the 1st time period as examples. The worst route situation $(0, 0, 0, 0, 0, 0)$ - none of the route is available for trucks; an ordinary route situation $(1, 0, 1, 1, 0, 0)$ - part of the routes are available for trucks, and the best route condition $(1, 1, 1, 1, 1, 1)$ - all of the route is available for trucks. Maximum additional helicopter's number in cases 1, 2, 3 are set as 20, 15 and 15, respectively. The procurement cost, rental cost, transportation cost, total cost of these 3 cases is shown in Table 6.

In order to satisfy each disaster area's demands, the rental cost of vehicles and the fuel cost are affected directly by the route conditions. For example, case 1 spends the most because of the high rent cost and fuel cost of helicopters. On the contrary, case 3 spends the least just as the good route condition which means we can meet the demands only by trucks.

In Fig. 4, the bottom line presents the lowest satisfied degree line. Even under the worst route condition, this model can offer more relief commodities than the lowest degree, which is reasonable in real life. The top line in Fig. 4

Table 6 Costs with different scenarios ($\beta=3$)

Stage 1		Stage 2			Stage 1 & 2
Case NO.	Procurement cost (\$)	Rental cost (\$)	Trans. cost (\$)	Penalty Cost (\$)	Total Costs (\$)
1	3689502	486822	55529	754298	4986151
2	3689502	457765	45071	629877	4822215
3	3689502	35100	959	430501	4156062

Fig. 4 Average satisfied proportion of 3 cases

is the average satisfied proportion under the best route condition. Apart from disaster area $j3$ (Jiangyou), the rest areas can receive almost the demands. One of the reason why $j3$ (Jiangyou) is provided less than other disaster areas is $j3$ (Jiangyou) is the furthest from the distribution center. The other reason is because of the amount of the total transported commodities are limited by the stocking amounts.

5. Conclusions

This study aimed to contribute to the existing literature by developing a new two-stage stochastic network flow model under practical assumptions that are rarely considered in previous similar papers, such as the fleet size, multiperiod of disaster relief operations, and a variety of un-certain data. A set of scenario is used which is based on all possible path combinations. As disasters are complex and unpredictable, the solutions provided by this mathematical model may not be fulfilled completely. However, the decision makers can adapt this 2-stage stochastic model into different disaster events by adjusting the value of the extra stocking coefficient β and the penalty coefficient η . For decision makers, they should weigh and consider the balance of the money, human resource and the mortality when disaster happens. This may be related with the severity of the disaster, the development condition of one country, rescue difficulty and so on.

To some natural disasters such as earthquakes and hurricanes, geographical condition has the greatest impact in all the criteria. It can affect the frequency of disaster happens, the rescue difficulty and even the reconstruction of each disaster area. Therefore, to combine some geographic data such as the Digital Elevation Model (DEM) data and other digitized topographic conditions with our model would be a challenging future work. With the scale of problem becoming larger, to solve the models more efficiently should also be considered.

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