Stochastic Location-allocation Modelling for Emergency Mobile Blood Collection

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Abstract: As an important humanitarian relief material after disaster, blood has its distinguishing characteristics like perishability and time-sensitivity. During the post-disaster emergency blood collection, the location and allocation of mobile blood collecting facilities directly influence the timely supply of blood. This paper proposes a two-stage bi-objective mixed integer location-allocation model for mobile blood collecting facilities. An augmented ε-constraint combined with Lagrangian relaxation method is applied. Finally numerical experiments based on blood collection process in Shanghai is provided. Copyright © 2019 IFAC

Keywords: Emergency blood collection, mobile blood collecting facilities, location-allocation problem, augmented ε-constraint, Lagrangian relaxation

1. INTRODUCTION

Blood transfusion plays a significant role in disaster relief and therefore, managing blood supply after a disaster is important for government health systems of every country. A disaster is referred to as an event that causes damage, destruction, loss of human life, human suffering and/or deterioration of health and health service (Najafi et al., 2013). Such events may involve various areas such as natural disasters (e.g., earthquakes, tsunamis, floods), terrorist attacks, food insecurity, infectious diseases, and poverty (Celik et al., 2012).

A surge in blood demand usually occurs after disasters, and governments tend to expand collection massively during the early days of disasters. Due to the uncertain decision environment and the inherited short shelf life of blood products, a large amount of excess blood will be discarded afterwards, causing severe wastage. After the 9.11 attack in America, 760000 units of blood was reported to be collected. However, more than 300000 units of the donated blood was never used until the expiration date (Silva et al., 2002). In the humanitarian relief for the 2008 Wenchuan earthquake in China, a large amount of blood was discarded because of excessive and unbalanced types of blood collection. In some blood banks, blood discard rate was reported ten times more than that in the normal situation (Yao et al., 2009).

These recent incidents have shown that it is very challenging for government health systems to manage post-disaster blood supply well. A blood supply chain (BSC) contains several echelons including blood collection, processing, inventory and distribution. Blood collection is the first step in the emergency BSC and mobile blood collecting facilities are the major means of blood collection in many countries. It is important to make location-allocation plans of these mobile facilities so as to provide effective and efficient support for the post-disaster blood supply system.

By proposing a two-stage bi-objective stochastic location-allocation model, this paper attempts to set effective and efficient plans for locating the mobile blood collecting facilities and allocating the donors to these facilities. Our goal is to minimize both the collection time and collection cost to meet the demands. The rest of the paper is organized as follows. Section 2 provides a literature review on related works. In section 3 and 4, the mathematical model and algorithm are presented. Numerical examples are discussed in section 5, and conclusions are provided in section 6.

2. RELATED WORK

The study of emergency blood supply chain (EBSC) falls into the field of humanitarian supply chain (HSC). Literatures on HSC and EBSC are both reviewed in this section.

2.1 Humanitarian Supply Chain

In location-allocation problems, usually facility location is considered as the pre-disaster stage decision and resource allocation is considered the post-disaster stage decision (Celik et al., 2012). Chang et al. (2007) presented a two-stage stochastic model to locate and distribute rescue resources for flood emergency. Mete and Zabinsky (2010) focused on the location and inventory decisions of medical supplies in post-earthquake Seattle. Mohammadi et al. (2016) established a three-objective model integrating pre and post-disaster decisions and solved it by a particle swarm optimization algorithm. Some other related mathematical models are presented by Ahmadi et al. (2015), Bozorgi-Amiri et al. (2011), Hasanzadeh et al. (2016), Moreno et al. (2016), Rawls et al. (2010), and Rezaei-Malek et al. (2016).

Scheduling problems usually consider resource collection and transportation in the post-disaster phase. Some literature applied single decision criterion, such as efficiency such as efficiency (Zhan et al., 2015) and effectiveness (Diabat et al., 2016). More literature considered multiple objectives. Sheu (2007) proposed a hybrid fuzzy clustering-optimization approach to group the demand points with similar degree of relief demand aiming at optimizing satisfactory rate and effectiveness. Huang et al. (2015) presented an integrated multi-objective optimization model combining resource allocation with emergency distribution. Pérez-Rodríguez et al. (2016) proposed an allocation-routing model for the optimal assignment of critical supplies after a disaster. Some literature also considered different disaster scenarios, such as Hu et al. (2016) and Zhan et al. (2015).

Routing problems usually optimize the last-mile delivery of transportation vehicles in HSC. Relevant models are developed by Berkoune et al. (2012), Hemmelmayr et al. (2010), Lin et al. (2011), and Rennemo et al. (2014).

2.2 Emergency Blood Supply Chain

Blood supply chain (BSC) has been widely studied since 1960s. Comprehensive reviews include Beliën and Forcé (2012), and Osorio et al. (2015). Most literature related to BSC addressed the location-allocation problem (Wang and Ma, 2015; Şahin et al., 2007), inventory management problem (Duan and Liao, 2014; Hosseinifard and Abbasi, 2016) and routing-scheduling problem (Gunpinar and Centeno, 2016; Zahiri et al., 2017).

Compared with the general BSC, the study of EBSC has attracted the attention of researchers only recently. Since in post-disaster phases, extremely uncertain environments, high response time requirements and perishability of blood products surely add to the difficulty of the problem. Sha and Huang (2012) studied post-earthquake blood collection. Their model aid in decision support for routing and scheduling temporary blood collecting facilities, but only considered cost as the objective. Kohneh et al. (2016) proposed a bi-objective programming model to locate post-disaster temporary blood collecting facilities and allocate them to permanent facilities. Fuzzy theory is used to address the uncertainty. Jabbarzadeh et al. (2014) presented a two-stage robust optimization model for the design of an EBSC. Fahimnia et al. (2015) developed a stochastic bi-objective blood supply network design model in disasters. ε-constraint and Larangian relaxation methods were applied. Salehi et al. (2017) proposed a two-stage robust stochastic EBSC model considering blood type substitution.

As the literature reveals, only a few studies have focused on blood collection in the EBSC design, and none of these works considered donation uncertainty and blood group compatibility. To fill the gap, a two-stage bi-objective stochastic model is developed in this study to support decision plans for location-allocation of mobile blood collection facilities. Donation uncertainty and blood group compatibility are both taken into consideration.

3. MATHEMTICAL MODEL

3.1 Problem Description

An emergency blood collection network (EBCN) in this model generally comprises donor groups (DG) $i \in I$, candidate locations for mobile facilities (MF) $j \in J$ and a blood centre (BC). Usually, MFs set out from the BC to a certain location to collect blood, and then deliver the collected blood back to the BC. In emergency collection, the location of a MF is considered flexible, which may change in each time period $t \in T$. Donors can be assigned to MFs within an acceptable geographic distance. The donated whole blood is tested and separated into different blood products at the BC. In this study, we focus on the location of MFs and allocation between DGs and MFs. The structure of our emergency blood collection model is shown in Fig. 1.
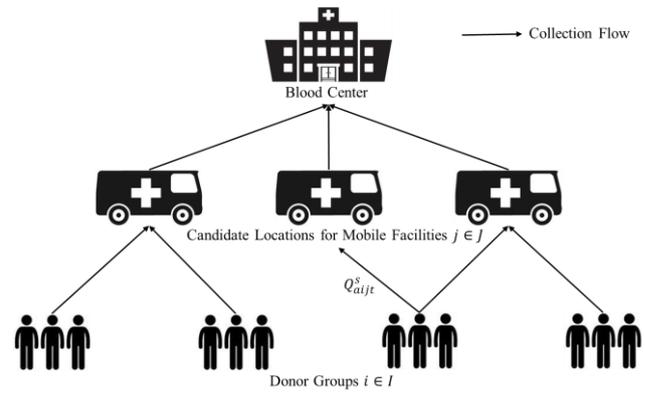

Fig. 1. The structure of emergency blood collection model.

The most commonly used product is red blood cells (RBC) so it's considered as the main product in our model. There are 8 ABO/Rhesus types of RBC and some of them can act as compatible substitution for each other in emergency cases. Table 1 shows the compatibility between each type of RBC.

Table 1. ABO/Rhesus compatibility of RBC

Donor	Recipient							
	O-	O+	A-	A+	B-	B+	AB-	AB+
O-	Y	Y	Y	Y	Y	Y	Y	Y
O+		Y		Y		Y		Y
A-			Y	Y			Y	Y
A+				Y				Y
B-					Y	Y	Y	Y
B+						Y		Y
AB-							Y	Y
AB+								Y

Y: compatible substitution

A bi-objective two-stage stochastic model considering blood type compatibility is presented in this work. Both collection cost and time are minimized. The first stage determines the location of each MF and the allocation of DGs to MFs when we only have a general prediction of the donation amount. Then in stage two when the actual donation amount is known, the blood amount at each candidate location and the blood amount used as matching or substitute type are determined.

3.2 Assumptions

- The location of each MF doesn't change within a time period due to the city's high donor density.

- More than one MF can stay at each candidate location at the same time.

- In each time period, the actual donor arrival and donation amount is considered stochastic.

- For each blood type, other types used as substitution for it must be smaller than a predefined proportion.

- The number of mobile facilities owned by the blood centre in each time period is considered as a constant.

3.2 Notations and Variables

Sets and indices

A	Set of blood types, $a, a' \in A$
I	Set of donor groups, $i \in I$
J	Set of candidate locations for mobile facilities, $j \in J$
T	Set of time periods, $t \in T$
S	Set of donor arrival scenarios, $s \in S$

Parameters

C	Capacity of a mobile facility
c^P	Penalty cost of each unit of unsatisfied demand
c_t^F	Setup cost of a mobile facility in period t
α	Upper limitation of blood substitution rate
$\beta_{aa'}$	$\beta_{aa'} \in \{0,1\}$, $\beta_{aa'} = 1$ if blood type a is a substitution of blood type a'; otherwise, $\beta_{aa'} = 0$
c_t^U	Unit blood collecting cost of a mobile facility in period t
t_t^U	Unit blood collecting time of a mobile facility in period t
c_{ijt}^T	Traveling cost from donor group i to candidate location j in period t
N	Maximum number of mobile facilities assigned by the blood center in each time period
d_a	Total demand of blood type a at the blood center
r_{ij}	Distance between donor group i and candidate location j
r^M	Maximum coverage distance of a blood facility
$\tilde{\rho}_s$	Probability of scenario s
$\tilde{q}_{aits}$	Number of arrived blood type a donors from donor group i in period t under scenario s

Decision variables

y_{jt}^{NF}	First stage variable indicating the number of mobile facilities at candidate location j in period t
x_{aijts}^{Q}	Second stage variable indicating the quantity of blood type a collected from donor group i at candidate location j in period t under scenario s
x_{as}^{MA}	Second stage variable indicating the quantity of blood type a used as matching under scenario s
$x_{aa's}^{SU}$	Second stage variable indicating the quantity of blood type a used as a substitute for type a' under scenario s

3.3 EBCN Model

The first stage objective function is to minimize mobile facility setup cost c^{FS} regarding variable y_{jt}^{NF}.

$$c^{FS}\left(y^{NF}\right) = \sum_j \sum_t c_t^F y_{jt}^{NF} \tag{1}$$

The second stage objective function minimizes blood collection cost c^{BC}, donor traveling cost c^{DT} and blood collection time t^{BC} with respect to variable x_{aijts}^{Q}.

$$c^{BC}\left(x^Q\right) = \sum_a \sum_i \sum_j \sum_t \sum_s \tilde{\rho}_s c_t^U x_{aijts}^Q \tag{2}$$

$$c^{DT}\left(x^Q\right) = \sum_a \sum_i \sum_j \sum_t \sum_s \tilde{\rho}_s c_{ijt}^T x_{aijts}^Q \tag{3}$$

$$t^{BC}\left(x^Q\right) = \sum_a \sum_i \sum_j \sum_t \sum_s \tilde{\rho}_s t_t^U x_{aijts}^Q \tag{4}$$

These can be further categorized into two objective functions indicating total blood collection cost and blood collection time.

$$f_1 = \min\left(c^{BC} + c^{DT} + c^{FS}\right) \tag{5}$$

$$f_2 = \min\left(t^{BC}\right) \tag{6}$$

s.t.

$$\sum_j y_{jt}^{NF} \leq N, \quad \forall t \tag{7}$$

$$\sum_j x_{aijts}^Q \leq \tilde{q}_{aits}, \quad \forall a,i,t,s \tag{8}$$

$$\sum_a \sum_i x_{aijts}^Q \leq C y_{jt}^{NF}, \quad \forall j,t,s \tag{9}$$

$$x_{aijts}^Q \leq 0, r_{ij} \geq r^M, \quad \forall a,i,j,t,s \tag{10}$$

$$x_{as}^{MA} + \sum_{a'} x_{aa's}^{SU} \leq \sum_i \sum_j \sum_t x_{aijts}^Q, \quad \forall a,s \tag{11}$$

$$x_{as}^{MA} + \sum_{a'} x_{a'as}^{SU} \geq d_a, \quad \forall a,s \tag{12}$$

$$\sum_{a'} x_{a'as}^{SU} \leq \alpha\left(x_{as}^{MA} + \sum_{a'} x_{a'as}^{SU}\right), \quad \forall a,s \tag{13}$$

$$x_{aa's}^{SU} \leq 0, \beta_{aa'} = 0, \quad \forall a,a',s \tag{14}$$

$$x_{aijts}^Q, x_{as}^{MA}, x_{aa's}^{SU} \geq 0 \tag{15}$$

$$y_{jt}^{NF} \geq 0 \text{ and integer} \tag{16}$$

Function (1) is the first stage objective function. Functions (2) to (4) represent second stage objective functions. Objective functions (5) and (6) minimize total cost and total time respectively. Constraint (7) ensures that in each time period, the total number of MFs at all candidate locations is no larger than the number of MFs assigned by the BC. Constraints (8) makes sure that the blood collected from each DG no larger than the donated quantity. Constraint (9) guarantees that the blood collected at a candidate location should be smaller than the total capacity of MFs sent there. Constraint (10) means that the distance from a DG to a MF must be within the

maximum accepted distance. Constraints (11) and (12) represent the balance between blood collection and demand, considering matching or substitute type. Constraint (13) guarantees that other blood types used as a substitute for each blood type should not exceed a certain proportion. Constraint (14) ensures the substitute types are compatible. Constraints (15) and (16) show the domain of the decision variables.

3.4 Model Transformation

The bi-objective model should be converted into a single-objective model. In this study, a posteriori ε-constraint method is used for it can address the vagueness of each objective function's relative importance and generate evenly distributed Pareto frontier. To save the time of validating the solutions in conventional ε-constraint method, an augmented ε-constraint introduced by Mavrotas (2009) is applied.

The first step, like the conventional ε-constraint method, is to optimize one of the objective functions, and use others as constraints of the model, shown as follows.

$$\min f_1 \tag{17}$$
$$s.t.$$
$$f_2 \le \varepsilon_2 \tag{18}$$
Constraints (7) to (16)

Then the lexicographic optimization is applied as follows: after getting the optima of the first objective function $\min f_1 = z_1^*$, $f_1 = z_1^*$ is added to the constraints to keep the solution of the previous optimization. Then we obtain $\min f_2 = z_2^*$. This process is repeated until all objective functions are finished and the payoff table is filled. Next the feasible solution range of each objective functions is divided into evenly distributed intervals. Thus evenly distributed Pareto optimal solutions can be obtained.

4. SOLUTION ALGORITHM

Usually we can't get the optimal solution directly from the relaxed model, but for minimum problem, the relaxed model offers a lower bound for the original model. By heuristic methods, an upper bound is obtained. Two bounds are updated until they are sufficiently close.

4.1 Starter Upper Bound

To get an initial upper bound as the starter, we can address each stage of the original two-stage model separately. Firstly consider a simple location problem without donation uncertainty and blood type substitution.

$$f_3 = \min \sum_j \sum_t c_t^F y_{jt}^{NF} \tag{19}$$
$$s.t.$$
$$q_{ait} = \sum_s \tilde{\rho}_s \tilde{q}_{aits}, \qquad \forall a,i,t \tag{20}$$
$$\sum_j y_{jt}^{NF} \le N, \qquad \forall t \tag{21}$$

$$\sum_j x_{aijt}^{QD} \le q_{ait}, \qquad \forall a,i,t \tag{22}$$
$$\sum_a \sum_i x_{aijt}^{QD} \le Cy_{jt}^{NF}, \qquad \forall j,t \tag{23}$$
$$\sum_i \sum_j \sum_t x_{aijt}^{QD} \ge d_a, \qquad \forall a \tag{24}$$
$$y_{jt}^{NF} \ge 0 \ and \ integer \tag{25}$$

Then fix $\bar{y}_{jt}^{NF} = y_{jt}^{NF}$ derived from above and find the solution to the original model, which is a feasible initial solution.

4.2 Lagrangian Lower Bound

By relaxing constraint (9) of the original problem, we can get the following Lagrangian dual problem.

$$\min L\left(u_{jts}\right) = \left(c^{BC} + c^{DT} + c^{FS}\right) + \sum_j \sum_t \sum_s u_{jts} \left(\sum_a \sum_i x_{aijts}^Q - Cy_{jt}^{NF}\right) \tag{26}$$
$$s.t.$$
Constraints (7) to (8), (10) to (16) and (18)

u_{jts} denotes a non-negative Lagrangian multiplier. By fixing the value of u_{jts}, we minimize objective (26). The solution obtained is infeasible for the original model but offers a lower bound to it.

4.3 Heuristic Upper Bound

Since constraint (9) is relaxed, in the solution derived from 4.2, the number of MFs sent out in each period is usually larger than the total number of available MFs, but a feasible solution can be obtained through heuristic modification.

Step 1: In each time period, obtain the smallest number of MFs needed $\left\lceil \sum_a \sum_i \sum_j x_{aijts}^Q / C \right\rceil$, where x_{aijts}^Q is derived from the Lagrangian dual.

Step 2: Let $y_t^M = \max_s \left\lceil \sum_a \sum_i \sum_j x_{aijts}^Q / C \right\rceil$, and keep y_t^M MFs in period t. The principle of which MF to keep is to see when filling the available capacity of MFs in each candidate location (derived from Lagrangian dual), which y_t^M MFs has the lowest donor traveling cost. Thus we get $\bar{y}_{jt}^{NF}$ in each candidate location in each time period.

Step 3: The blood collected from other candidate locations other than the kept y_t^M MFs in the Lagrangian dual can be shifted to these MFs by solving the following model.

$$f_4 = \min \left(c^{BC} + c^{DT} + c^{FS}\right) \tag{27}$$
$$s.t.$$
$$\sum_a \sum_i x_{aijts}^Q \le C\bar{y}_{jt}^{NF}, \qquad \forall j,t,s \tag{28}$$

Constraints (8), (10) to (15) and (18)

The resulting feasible solution provides an upper bound for the original model.

4.4 Lower and Upper Bound Update

If the gap between the obtained lower and upper bound is within a predefined tolerance, an acceptable solution to the original model is found. Otherwise, the Lagrangian multiplier u_{jts} is updated and new bounds are generated. The sub-gradient method to update u_{jts} was proposed by Fisher (2004). Suppose we are in the iteration $(n+1)$.

$$u_{jts}^{n+1} = \max \left\{ 0, u_{jts}^n - stepsize^n \left(\sum_a \sum_i x_{aijts}^Q - Cy_{jt}^{NF} \right) \right\} \quad (30)$$

define

$$stepsize^n = \frac{\lambda^n (upperbound - lowerbound^n)}{\sum_j \sum_t \sum_s \left(\sum_a \sum_i x_{aijts}^Q - Cy_{jt}^{NF} \right)^2} \quad (31)$$

where *upperbound* represents the best upper bound within previous iterations and *lowerbound*^{n} represents the lower bound obtained in iteration n. The initial λ is set to be 0.5. If *lowerbound*^{n} doesn't improve in an iteration, λ is halved. To avoid oscillation of *lowerbound*^{n}, a method developed by Crowder (1974) is applied. Define dir_{jts}^n to be the direction vector of iteration n. Let $dir_{jts}^{n+1} = u_{jts}^{n+1} + \tau dir_{jts}^n, 0 \le \tau \le 1$. Here we set $\tau = 0.7$ and use dir_{jts}^n as the step direction instead of the sub-gradient direction u_{jts}.

5. COMPUTATIONAL RESULTS

Based on the blood collection system in Shanghai (number of MFs, candidate locations), test experiments of different disaster scales are designed. Table 2 shows the data size. The model and algorithm are run with CPLEX 12.7.

Table 2. Data size of test experiments

DGs	Candidate locations	MFs	Time periods	Scenarios
30	25	15	5	4

4 random data sets are generated in the above data size. Table 3 shows the results.

Table 3. Results of test experiments

	Data set 1		
	Lagrangian	CPLEX	
Pareto solution	Cost	Cost	Gap
1	652987.5	646014.75	1.08%
2	653216.38	646472.5	1.04%
3	653715.94	647570.5	0.95%
4	654573.31	650158.75	0.68%
5	656363.25		
Pareto solution	Time	Time	Gap
1	65.69	65.65	0.06%
2	65.51	64.5	1.57%
3	65.32	63.44	2.96%
4	65.14	62.31	4.54%
5	64.95		
	Runtime	Runtime	Gap
	146.015	4345.5	29.76064
	Data set 2		
	Lagrangian	CPLEX	
Pareto solution	Cost	Cost	Gap
1	711476.5	704399	1.00%
2	711776.25	704710.3	1.00%
3	712615.88	705318.5	1.03%
4	713930.5	706590.75	1.04%
5	716052.75	709003.5	0.99%
Pareto solution	Time	Time	Gap
1	71.54	71.44	0.14%
2	71.22	70.6	0.88%
3	70.91	69.71	1.72%
4	70.59	68.9	2.45%
5	70.27	68.07	3.23%
	Runtime	Runtime	Gap
	202.11	5872.719	29.05704
	Data set 3		
	Lagrangian	CPLEX	
Pareto solution	Cost	Cost	Gap
1	754745.25	747454.25	0.98%
2	755358.56	747826	1.01%
3	756716.25	748842.5	1.05%
4	759113.37		
5	763331		
Pareto solution	Time	Time	Gap
1	76.16	75.83	0.44%
2	75.73	74.67	1.42%
3	75.29	73.68	2.19%
4	74.85		
5	74.42		
	Runtime	Runtime	Gap
	119.685	4166.953	34.816
	Data set 4		
	Lagrangian	CPLEX	
Pareto solution	Cost	Cost	Gap
1	813550	804221.25	1.16%
2	813964.63	804517.75	1.17%
3	815190.81	806082.25	1.13%
4	817300.44	809046	1.02%
5	821012.5	816266	0.58%
Pareto solution	Time	Time	Gap
1	82.34	81.74	0.73%
2	81.99	80.6	1.72%
3	81.64	79.47	2.73%
4	81.29	78.34	3.77%
5	80.94	77.21	4.83%
	Runtime	Runtime	Gap
	253.767	4894.75	19.28836295

We can see that the collection cost gaps obtained by the Lagrangian heuristic are all within 1.3% from the real optima. The collection time gaps are larger (all within 5%) but since the total time is small, the results are still very close. Most importantly, the running time is improved greatly by 20 to 35 times shorter. The results have shown that our algorithm can provide a set of near-optimal Pareto solutions in a short time.

6. CONCLUSIONS

This study contributes to humanitarian logistics by presenting a stochastic bi-objective location-allocation model for timely and cost-saving blood collection during post-disaster period. Augmented ε-constraint method combined with Lagrangian relaxation-based heuristics are used to solve the model timely. Numerical experiments based on a real blood collection system demonstrate that our model and algorithm address the EBCN mobile facility location-allocation problem well.

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