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Supply Allocation and Vehicle Routing Problem with Multiple Depots in Large-Scale Emergencies*

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1. Introduction

Large-scale emergencies, such as substantial acts of nature, large human-caused accidents, and major terrorist attacks, are of high-consequence, low-probability (HCLP) events that may result in loss of life and severe property damage. In recent years, developing decision-oriented operations research models to improve preparation for and response to major emergencies has drawn more and more attention (see Altay & Green (2006) and Larson et al. (2006)).

Relief resources play an important role in emergency management after disasters, such as medicine, food, tent, etc. Due to scarce resources and overwhelming demands during an emergency (especially in the early stages) careful pre-planning and efficient execution can save lives. A key factor in an effective response to an emergency is the prompt availability of necessary supplies at emergency sites. Therefore, efficient emergency logistics becomes important in addressing and optimizing the complex distribution process. In most real-life situations, the distribution process is typically divided into two decision stages. In the first stage, supply quantity allocated to each demand location is determined. This is referred to as the allocation problem. In the second stage, how supplies will be transported is determined, which may be modeled as a Vehicle Routing Problem. Obviously, when supply is large enough, the allocation problem is trivial, while the second stage is still a complex problem.

Traditional Vehicle Routing Problem (VRP) is to design the least cost routes for a vehicle fleet to supply goods from inventory to customer locations. The problem was first introduced by Dantzig & Ramser (1959) to solve a real-world application concerning the delivery of gasoline to service stations. A comprehensive overview of the VRP can be found in Toth & Vigo (2002) and other general surveys on the deterministic VRP can also be found in Laporte (1992). Various specific VRP models, e.g. with time windows, multiple depots, dynamic routes, and stochastic customer demands, etc. were published in Rathi et al. (1993) and Renaud et al. (1996). Astrid & David (2003) considered vehicle routing problem with random travel time and service time, while all vehicles departed from the same depot. Enrico & Maria (2002) considered periodic vehicle routing problem (PVRP) while vehicles can renew their capacity at some intermediate facilities. Recently, an exact algorithm was presented for PVRP in

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Roberto et al. (2011). Dynamic request occurrence is considered in Lorini et al. (2011). Almost all VRP models and algorithms are for "normal operation" that minimize cost represented by travel distances or travel times and applied in daily operating logistic systems. Only several works considered total arrival time (see Campbell et al. (2008) and Ngueveu et al. (2010)).

The highly unpredictable nature of large-scale emergencies, unfortunately, leads to significant uncertainty both in demand and travel times. For example, in certain emergency cases, medication or antidotes must be applied within a specific time limit from the occurrence of the event to maximize their effectiveness to save lives. Requirement for the medication may change rapidly along with the case development and is hard to predict. Traditional pharmaceutical supply chains are no longer adequate to provide the rush demand. In emergency cases the so called Strategic National Stockpile, a large managed inventory from manufacturers, may be used. Vehicle fleet size can be uncertain due to emergency calls. The vehicles may load supply from multiple depots (e.g. airports) and may not return to the original depot location. Travel times of transporting the medication from the central supply to the demand population areas also become uncertain in case of emergency because of sudden road congestion and panic, or because of strict traffic control. Thus, the objectives of the VRP for response to emergency are usually to minimize both the unmet demand and delay time. Finally, an efficient algorithm to find a good solution is very important for emergency operation managers.

As discussed above, transportation is an important issue in emergency response, which is called emergency logistics. Emergency logistics management has also emerged as a worldwide-noticeable theme. Sheu (2007) presented four main challenges under which emergency logistics management can be characterized. Also as a sponsor, Sheu edited a special issue of Transportation Research Part E, in which six papers on emergency logistics were included. These papers concentrated on addressing the issue of relief distribution to affected areas. Consignment of supply is typically examined in the literature as a multi-commodity network flow problem, with a multi-period and/or multi-modal setting. Haghani & Oh (1996) formulated a multi-commodity, multi-modal network flow model with time windows for disaster response. Two heuristic algorithms were proposed. The flow of supply over an urban transportation network was modeled as a multi-commodity, multi-modal network flow problem by Barbarosoglu & Arda (2004). A two-stage stochastic programming framework is formed as the solution approach. Another study on the topic, conducted by Fiedrich et al.(2000), model the problem similar to a machine scheduling problem proposing two heuristics, Simulated Annealing and Tabu Search. Yi & Ozdamar (2004) considered a dynamic and fuzzy logistics coordination model for conducting disaster response activities. The model was illustrated on an earthquake data set from Istanbul. Also, Barbarosoglu & Arda (2004) proposed that their model could be used effectively within a decision-aid tool by public and non-public response agencies that are obscured by the variability of impact estimations under large number of different earthquake scenarios.

All these uncertain factors must be considered by an emergency operation manager in dispatching vehicles to effectively deliver the life-saving demands to the people in need. Due to the characteristics of uncertainty of large-scale emergency, a dynamic VRP can be stated as follows:

1. when an emergency occurs, with reported demand calls, a responder must evaluate the demand pattern, including locations, quantity, and time requirement for the deliveries.
2. organize the supplies and route the available vehicles to meet the emergency requirements in an efficient way to minimize the unmet demand and the total time delay.
3. with the updated demand information, relocate medical supplies and vehicles, route and dispatch next fleet with the same objective.
4. keep evaluating the updated demand and routing further vehicles, until all the demand is met.

Shen et al. (2007) studied a stochastic VRP model with time windows that minimize unmet demand for large-scale emergencies. In their paper, vehicle time delay is not allowed when visiting a demand node. However this strict limitation may be unreasonable because in emergency situations even the urgency of need for medical supplies may not be met from a time perspective. The dispatcher will still send the supply to save as many lives as possible with the least time delay. Liu et al. (2007) considered both the unmet demand and time delays.

This paper focuses on modeling and solution framework for the VRP in response to a large-scale emergency. In Section 2, a deterministic VRP model with multiple depots will be presented. In section 3, this model will be analyzed in detail. Then, an efficient heuristic algorithm is designed for the proposed model in Section 4. Finally in Section 5,, numerical experiments and a case simulation demonstrate that the model and algorithm can be very useful as a decision tool for emergency responders.

2. A deterministic VRP model with multiple depots

In this paper, we consider a situation that several fleets of vehicles send emergency supply from multiple depots (e.g. airport or central inventory) to demand locations (e.g. hospitals or triage stations), and return to the original depots after delivery all the supply. Objectives of the model is to minimize the maximum unsatisfied rate and the total weighted time delay.

According to emergency conditions, we have several assumptions:

1. There is limited amount of supply in each depot.
2. Each demand node has a deadline for supply, and delay is permitted.
3. The traveling time between each pair of nodes is deterministic.
4. Vehicles are not reusable.

In the model presented in this paper, the total weighted time delays are explicitly expressed in the objective function as the most important factor.

Now, decision variables and parameters will be specified.

Set D represents demand nodes. L is denoted as supply set including depots and other suppliers. We consider fleet sets $K(l)$ of vehicles at supplier l. Let $K = \bigcup_{l \in L} K(l)$ for simplification. The node set is expressed as $C = D \bigcup L$. Suppose from each node i to any other node j there is a route, or an arc (i, j). Therefore a transport network can be expressed by the node set $C = D \bigcup L$ and arc set $\{(i, j), i, j \in C, i \neq j\}$.

Parameters:

n : number of available vehicles;
s_l : total available supply at depot l;
c_k : the maximum load of vehicle k;
d_i : the latest arrival time required by demand node i, or the expected deadline for node i;
τ_{ijk} : the estimated time to traverse arc (i,j) for vehicle k;it is set to ∞ for nonexistent links;
ζ_i : amount of commodity needed at node i;

Decision Variables:

X_{ijk} : a binary flow variable, equal to 1 if (i,j) is traversed by vehicle k and 0 otherwise;
Y_{ik} : delivery by vehicle k to the demand node i, integer value is assumed;
U_i : amount of unsatisfied demand at node i;
T_{ik} : time at which vehicle k arriving at node i, the unload time is negligible; and
δ_{ik} : delay time happened when vehicle k sends supply to node i.
If k arrives $i$later than d_i, then $\delta_{ik} > 0$.

Vehicle scheduling should be made so as to minimize the next two objectives. The first one is maximum unsatisfied rate among all demand points. This objective tries to create fairness among all demand points.

$$max\{\frac{U_i}{\zeta_i}, i \in D\} \tag{1}$$

The second one is total weighted time delay. Here, δ_{ik} is the time delay and Y_{ik} is the amount of supply arriving at node i. Total weighted time delay is the product of these two variables. This objective forces supply to arrive before due date.

$$\sum_{i \in D, k \in K} Y_{ik}\delta_{ik} \tag{2}$$

The vehicle routing model (VRM) for emergency supply allocation and transportation with multi-suppliers is formulated as follows:

$$\textbf{min } z_1 = max\{\frac{U_i}{\zeta_i}, i \in D\} \tag{3}$$
$$\textbf{min } \quad z_2 = \sum_{i \in D, k \in K} Y_{ik}\delta_{ik} \tag{4}$$

subject to

$$\sum_{l \in L} \sum_{k \in K(l)} \sum_{j \in D} X_{ljk} \leq n \tag{5}$$
$$\sum_{j \in C} X_{ijk} = \sum_{j \in C} X_{jik} \leq 1 \quad (\forall i \in C, k \in K) \tag{6}$$
$$\sum_{i \in S} \sum_{j \in C \setminus S} X_{ijk} \geq 1 \quad (\forall S \subseteq D, k \in K) \tag{7}$$
$$\sum_{l \in L} \sum_{j \in C} X_{ljk} \leq 1 \quad (\forall k \in K) \tag{8}$$
$$\sum_{k \in K(l)} T_{lk} = 0 \quad (\forall l \in L) \tag{9}$$

$$0 \le T_{ik} + \tau_{ijk} - T_{jk} \le (1 - X_{ijk})M \quad (\forall i \in C, j \in D, k \in K) \tag{10}$$

$$0 \le T_{ik} - \delta_{ik} \le d_i \sum_{j \in C} X_{ijk} \quad (\forall i \in D, k \in K) \tag{11}$$

$$\delta_{ik} \le M \sum_{j \in C} X_{ijk} \quad (\forall i \in D, k \in K) \tag{12}$$

$$s_l - \sum_{k \in K(l)} \sum_{i \in D} Y_{ik} \ge 0 \quad (\forall l \in L) \tag{13}$$

$$\sum_{i \in D} Y_{ik} \le c_k \quad (\forall k \in K) \tag{14}$$

$$Y_{ik} \le c_k \sum_{j \in D} X_{ijk} \quad (\forall i \in D, k \in K) \tag{15}$$

$$\sum_{k \in K} Y_{ik} + U_i - \zeta_i \ge 0 \quad (\forall i \in D) \tag{16}$$

$$X_{ijk} = \{0, 1\}; T_{ik} \ge 0; Y_{ik} \ge 0; U_i \ge 0; \delta_{ik} \ge 0; \tag{17}$$

The objective of the model is to minimize maximum unsatisfied rate among all demand points and the total weighted time delay. Constraint set (5) specifies that the number of vehicles to service must not exceed the available fleet size. Constraint (6) indicates that each vehicle visits one demand point at most once and the vehicle must leave the demand node without staying there. Constraints (7) are the subtour elimination constraints. A vehicle cannot go to another depot according to constraint (8). This feasible route constraint allow split delivery. Constraints (9)-(12) are time-window constraints that guarantee schedule feasibility with respect to time considerations. Once a vehicle arrives at a demand point later than the required deadline, a penalty $\delta_{ik} \ge 0$ is observed. (13)-(16) state the construction on the commodity flows, while constraint (17) specifies the binary and integer variables.

3. Model analysis

We will prove the above (VRM) problem is NP-hard by showing that the traveling salesman problem(TSP) is a special case of the VRM.

Theorem 1. *The VRM is NP-hard even if there is only one depot with one vehicle.*

Proof. We will construct a special case of VRM, which is a TSP. First, assume that there is only one depot and m demand nodes. Each demand node needs one unit of medical supply with deadline 0. Also assume there is only one vehicle with capacity m at the depot to deliver all m units to the demand nodes. The object is to minimize the total time delay. Under these assumptions the VRM becomes a TSP.

The VRM is a multi-objective model and there are two objectives: maximum unsatisfied rate and total weighted time delay. If we ignore the second objective, WRM can be solved in polynomial time. At first, let's consider the following model:

$$\mathbf{min} \quad max\{\frac{U_i}{\zeta_i}, i \in D\} \tag{18}$$

subject to

$$\sum_{i \in D} (\zeta_i - U_i) \leq \sum_{l \in L} s_l \tag{19}$$
$$U_i \geq 0 \tag{20}$$

This is a supply allocation model (SAM). By using a simple technique, the SAM can be transformed to the following model:

$$\textbf{min} \quad \eta \tag{21}$$

subject to

$$\frac{U_i}{\zeta_i} \leq \eta, \quad (\forall i \in D) \tag{22}$$
$$\sum_{i \in D} (\zeta_i - U_i) \leq \sum_{l \in L} s_l \tag{23}$$
$$U_i \geq 0, \eta \geq 0 \tag{24}$$

Obviously, this is a linear programming model. It means VRM without the second objective can be easily solved within constraints (5-17).

In many situations, the data such as U_i, ζ_i, s_l in model SAM are integers. Then the supply allocation model with integer constraints (SAMI) is as follows.

$$\textbf{min} \quad \eta \tag{25}$$

subject to

$$\frac{U_i}{\zeta_i} \leq \eta, \quad (\forall i \in D) \tag{26}$$
$$\sum_{i \in D} (\zeta_i - U_i) \leq \sum_{l \in L} s_l \tag{27}$$
$$U_i \geq 0 \text{ and integer}, \eta \geq 0 \tag{28}$$

Next, we will propose an LP-rounding algorithm for the above model and show that this algorithm can find the optimal solution in polynomial time.

Algorithm LPrA LP-ROUNDING ALGORITHM FOR SAMI

1. obtain the LP-relaxation of SAMI by deleting all integer constraints.
2. solve LP-relaxation, and get fractional optimal solution (U_i^*, η^*).
3. **for** each U_i^*
4. $\quad U_i = \lceil U_i^* \rceil$
5. **endfor**
6. $a = \sum_{l \in L} s_l - \sum_{i \in D} (\zeta_i - U_i)$
7. **while** $a > 0$
8. $\quad$ **for** each $i \in D$

9. $\eta_i = \frac{U_i}{\zeta_i}$
10. **endfor**
11. $\eta = \max_{i \in D}\{\eta_i\}$
12. choose $k \in \{i | \eta_i = \eta\}$
13. $U_k = U_k - 1$
14. $a = a - 1$
15. **endwhile**
16. $\eta = \max_{i \in D}\{\eta_i = \frac{U_i}{\zeta_i}\}$
17. $Q = \{i | \eta_i > \eta^*, \frac{U_i+1}{\zeta_i} < \eta\}$
18. **while** $Q \neq \Phi$
19. choose j such that $\eta_j = \eta$
20. choose k such that $\frac{U_k+1}{\zeta_k} = \max_{i \in Q}\{\frac{U_i+1}{\zeta_i}\}$
21. $U_k = U_k + 1$
22. $U_j = U_j - 1$
23. $\eta = \max_{i \in D}\{\eta_i = \frac{U_i}{\zeta_i}\}$
24. $Q = \{i | \eta_i > \eta^*, \frac{U_i+1}{\zeta_i} < \eta\}$
25. **endwhile**
26. Output the integer solution U_i and unsatisfied rate η.

Theorem 2. *The algorithm LPrA can find the optimal solution for SAMI in $O(n^2)$ time.*

Proof. First, we will show the algorithm LPrA can stop within $O(n^2)$. According to the definition of a, step 8-14 runs at most n times for $a < n$. Step 11 runs at most n times. Then the total running time from step 7 to 15 is at most n^2. Simultaneously, step 18-25 runs also at most n^2.

Second, we will prove the output solution is optimal by contradiction. Let $\{U_1, U_2, \ldots, U_n\}$ and η be the output solution of the algorithm LPrA. Then for $1 \leq i \leq n$, $\eta_i = \frac{U_i}{\zeta_i} \leq \eta$. Without loss generality, suppose $\eta_k = \eta$. Now, suppose $\{U_1^*, U_2^*, \ldots, U_n^*\}$ and η^* are the optimal solution of SAMI problem, which satisfies $\eta^* < \eta$. Let $\eta_j^* = \eta^*$ without loss of generality. We have $\eta_k = \eta > \eta^* \geq \eta_k^*$, then $U_k > U_k^*$. On the other hand, $\sum U_k = \sum U_k^*$, then there must exit l such that $U_l < U_l^*$. So $\eta_l < \eta_l^* \leq \eta^* < \eta = \eta_k$ holds. Then, $\frac{U_l+1}{\zeta_l} \leq \eta_l^* < \eta$, $l \in Q$ according to step 17 in algorithm LPrA, a contradiction.

Then, the complexity of VRM is totally up to the second objective, while this model for the second objective is a vehicle routing problem. In the next section, we will propose a local search algorithm.

4. Local search algorithm

Define a supply capability for each depot:

$$M_l = min\{s_l, \sum_{k \in K(l)} c_k\} \quad (\forall l \in L)$$

The total supply capacity is:

$$M = \sum_{l \in L} M_l$$

Let $\zeta = \sum_{i \in D} \zeta_i$, then we have the next three situations.

1. When $\zeta - M > 0$, this represents that there is not sufficient capacity to deliver all the commodity to the demanding nodes.
2. When $\zeta - M = 0$, there is a balanced capacity for supply and demand.
3. When $\zeta - M < 0$, there is still surplus capacity.

Let $\theta = max\{\zeta - M, 0\}$. When $\theta = 0$, the demand in each node is satisfied.

Before presenting our algorithm, we assume that $|K| < |D|$, i.e. the number of vehicles is less than the number of demand nodes, otherwise the problem will be trivial. We also assume that the route distances (or travel times) follow the triangle inequality, i.e. the direct distance or travel time between any two nodes is less than that through a third node.

The local search algorithm can be divided into two stages: medical allocation and vehicle routing. First, the amount of medical supplies allocated to each node are determined by using algorithm LPrA. Then using a greedy algorithm the vehicles are scheduled. The details of the algorithm are as follows.

Local search algorithm

Step 1: Obtain the amount of supply allocated to each node by using algorithm LPrA, ζ_i'.

Step 2: Let $P = \{p_k\}$ specify the current position of vehicle $k \in K$. Let $U_i = \zeta_i', i \in D$ and let $p_k = l, k \in K(l)$ to specify the vehicles departing from depot l, ($\forall l \in L$). $T_{lk} = 0$, $\theta = max\{\sum_{i \in D} \zeta_i' - M, 0\}$.

Step 3: Let $Q = \{i | U_i > 0\}, K = \{k | c_k > 0\}$.

For all $i \in Q, j \in K$, compute

$$\delta_{ij} = max\{0, T_{p_j} + \tau_{p_j ij} - d_i\}$$

$$Y_{ij} = min\{c_j, U_i\}$$

Find

$$(q, k) \in \{(i, j) | Y_{ij}\delta_{ij} = min_{i \in Q, j \in K}\{Y_{ij}\delta_{ij}\}\}$$

Update

$$\begin{aligned} X_{p_k qk} &:= 1 \\ p_k &:= q \\ Y_{p_k k} &:= \min\{U_{p_k}, c_k\} \\ c_k &:= c_k - Y_{p_k k} \\ U_{p_k} &:= U_{p_k} - Y_{p_k k} \end{aligned}$$

Step 4: If $\sum_{i \in D} U_i = \theta$, then $X_{p_k lk} = 1, Y_{lk} = c_k, \forall k \in K(l), l \in L$, stop; otherwise go to Step 3.

5. Simulation

Based on the above model and algorithm, we simulate an emergency situation when a pandemic disease (e.g. SARS) happens in Beijing, China and a certain quantity of medication need to be delivered from the airport and Beijing Emergency Medical Center(EMC) to major downtown hospitals as soon as possible. Name of 16 hospitals and their locations are shown in Table 1 and Figure 1. The distance are shown in table 2. Suppose we have a fleet of 5 identical

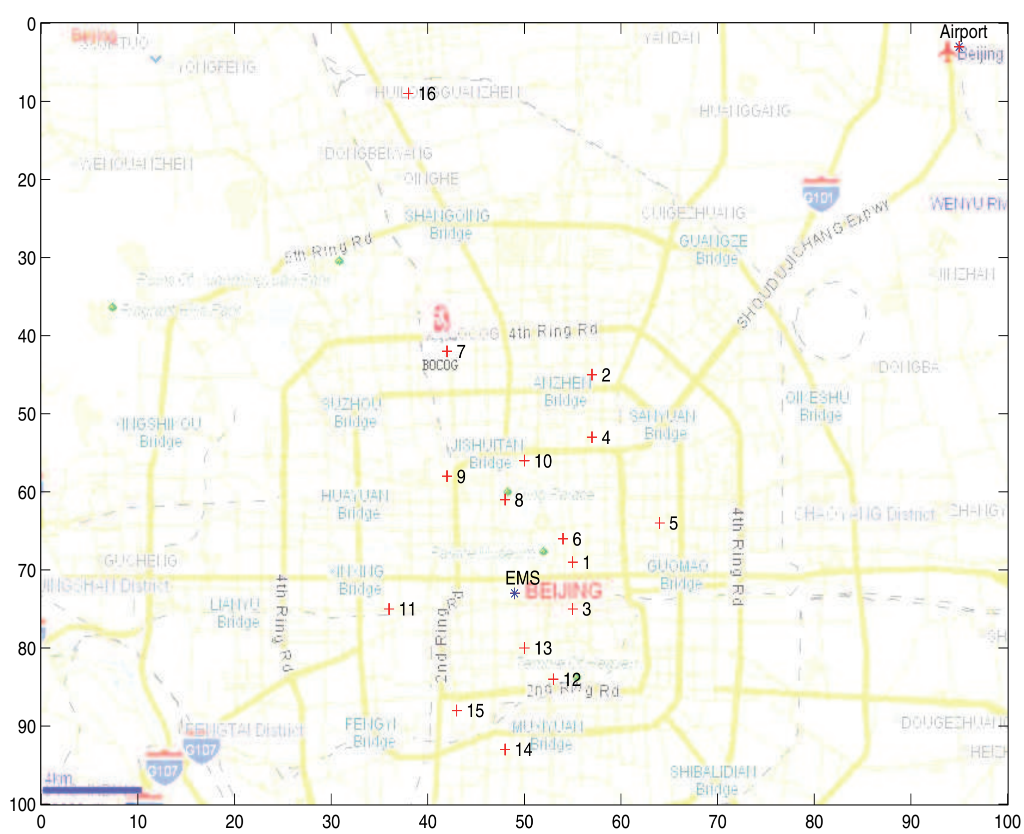

Fig. 1. Hospitals, Airport and EMC in Beijing

trucks in the airport and 3 at the EMC to do the delivery. The capacity of each truck is 25. The average speed of each truck is 40 kilometers per hour. According to the distance matrix, we can obtain the travel time between each pair of nodes. All time units will be represented in minutes. All case study settings are solved on a Windows XP-based Pentium(R) 4 CPU 2.93CHz personal computer using MATLAB 7.0 and its Optimization Toolbox.

There are 125 units of medication at the airport and 75 units at the EMC that need to be sent to the 16 hospitals. The demand and deadline in each hospital are generated randomly from a uniform distribution.

In the first case study, the deadlines are fixed, and we simulate the algorithm 30 times with different demand randomly generated from a uniform distribution. Deadlines are shown in Table 3. Demand in each hospital is generated randomly between 1 to 25 from a uniform

label	hospital
1	Peking Union Medical College Hospital (PUMCH)
2	China-Japan Friendship Hospital (CJFH)
3	Beijing Tongren Hospital (BTrH)
4	Beijing Ditan Hospital (BDH)
5	Beijing Chaoyang Hospital (BCH)
6	Beijing Obstetrics and Gynecology Hospital (BOGH)
7	Peking University Third Hospital (PUTH)
8	Peking University First Hospital (PUFH)
9	Peking University People Hospital (PUPH)
10	Beijing Ji Shui Tan Hospital (BJSYH)
11	Beijing Shijitan Hospital (BSH)
12	Beijing Tiantan Hospital (BTtH)
13	Beijing Friendship Hospital (BFH)
14	China Rehabilitation Research Center (CRRC)
15	Beijing Youan Hospital (BYH)
16	Beijing Hui Long Guan Hospital(BHLGH)

Table 1. Hospitals and their labels

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Airport
PUMCT	0	8	1.2	10.6	5	2	12.8	5.7	8.4	7.5	9.1	6.3	5.4	10.4	10.1	21.94	26.36
CJFH	8	0	8.8	4.4	7.8	8.2	7.7	8.8	9.8	8	16.6	13.8	13	21.6	18.4	16.63	22.67
BTrH	1.2	8.8	0	12	5.8	3	13.8	6.6	9.5	8.4	9.4	5	4.4	9	9.5	24.26	27.51
BDH	10.6	4.4	12	0	7.1	4.4	7.8	5.2	6.2	4.3	13	12.5	11.2	20	14.9	17.15	23.91
BCH	5	7.8	5.8	7.1	0	5.1	14.4	7	9.8	8.8	13.8	11.2	10.4	15.3	16.1	19.32	23.73
BOGH	2	8.2	3	4.4	5.1	0	11	3.7	6.5	5.4	9.2	6	5.3	10.8	11.2	21.21	29.14
PUTH	12.8	7.7	13.8	7.8	14.4	11	0	7.5	5.8	6	12.6	17	14.3	17.8	16	11.83	27.72
PUFH	5.7	8.8	6.6	5.2	7	3.7	7.5	0	2.8	1.7	8.5	8	7.6	11.1	9.34	17.73	27.73
PUPH	8.4	9.8	9.5	6.2	9.8	6.5	5.8	2.8	0	3.4	6.8	11.6	9	13.6	8.77	15.66	28.94
BJSYH	7.5	8	8.4	4.3	8.8	5.4	6	1.7	3.4	0	9.4	8.2	8.8	16	9.94	16.49	26.81
BSH	9.1	16.6	9.4	13	13.8	9.2	12.6	8.5	6.8	9.4	0	12	8.7	13.1	7.2	24.65	35.79
BTtH	6.3	13.8	5	12.5	11.2	6	17	8	11.6	8.2	12	0	1.8	4.9	4.6	26.86	32.63
BFH	5.4	13	4.4	11.2	10.4	5.3	14.3	7.6	9	8.8	8.7	1.8	0	6.5	4.88	24	32.12
CRRC	10.4	21.6	9	20	15.3	10.8	17.8	11.1	13.6	16	13.1	4.9	6.5	0	4.8	27.58	37.24
BYH	10.1	18.4	9.5	14.9	16.1	11.2	16	9.34	8.77	9.94	7.2	4.6	4.88	4.8	0	24.56	37.29
BHLGH	21.94	16.63	24.26	17.15	19.32	21.21	11.83	17.73	15.66	16.49	24.65	26.86	24	27.58	24.56	0	32.34
Airport	26.36	22.67	27.51	23.91	23.73	29.14	27.72	27.73	28.94	26.81	35.79	32.63	32.12	37.24	37.29	32.34	0
EMC	4.74	13.6	3.53	9.71	10.41	4.57	12.32	5.06	5.49	5.74	5.69	4.26	2.61	7.49	6.67	34.35	33.66

Table 2. Distance between hospitals, Airport and EMC (Kilometer)

distribution. In the second case study, demand is fixed, then we simulate the algorithm 30 times with different deadline randomly generated. Demand is shown in Table 5. Deadline in each hospital is generated randomly between 40 to 90 minute from a uniform distribution.

hospital	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
deadline	43	44	73	50	83	49	49	90	62	58	56	59	60	70	46	42

Table 3. Fixed deadline of each hospital(minutes)

Problem No.	total supply	total unsatisfied demand	total weighted time delay	maximum unsatisfied rate
1	200	7	1370	0.0667
2	200	6	433	0.0526
3	200	14	193	0.1111
4	200	0	260	0
5	200	61	441	0.2500
6	200	21	949	0.1304
7	200	20	260	0.1200
8	200	0	452	0
9	200	0	48	0
10	200	0	499	0
11	200	38	1443	0.2000
12	200	0	599	0
13	200	3	376	0.0476
14	200	38	620	0.1875
15	200	16	1499	0.1176
16	200	15	99	0.1000
17	200	51	356	0.2353
18	200	3	228	0.0500
19	200	0	806	0
20	200	52	16	0.2381
21	200	31	198	0.1667
22	200	0	161	0
23	200	0	416	0
24	200	2	1120	0.0417
25	200	25	445	0.1500
26	200	0	585	0
27	200	0	54	0
28	200	4	627	0.0455
29	200	0	18	0
30	200	72	350	0.2857
average value	200	15.9667	497.3667	0.0866

Table 4. Simulation results

hospital	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
demand	13	25	10	14	5	13	11	17	17	24	5	3	15	25	1	22

Table 5. Fixed demand of each hospital

Problem No.	total supply	total unsatisfied demand	total weighted time delay	maximum unsatisfied rate
1	200	20	0	0.12
2	200	20	660	0.12
3	200	20	321	0.12
4	200	20	422	0.12
5	200	20	880	0.12
6	200	20	63	0.12
7	200	20	338	0.12
8	200	20	0	0.12
9	200	20	346	0.12
10	200	20	204	0.12
11	200	20	272	0.12
12	200	20	28	0.12
13	200	20	45	0.12
14	200	20	21	0.12
15	200	20	201	0.12
16	200	20	223	0.12
17	200	20	87	0.12
18	200	20	33	0.12
19	200	20	1261	0.12
20	200	20	46	0.12
21	200	20	233	0.12
22	200	20	237	0.12
23	200	20	109	0.12
24	200	20	6	0.12
25	200	20	312	0.12
26	200	20	432	0.12
27	200	20	40	0.12
28	200	20	188	0.12
29	200	20	725	0.12
30	200	20	60	0.12
average value	200	20	259.7667	0.12

Table 6. Simulation results

From these two computational cases, the following observations can be made.

- For fixed deadline cases, the average maximum unsatisfied rate is 0.0866. Medical supplies are allocated equitably. The same conclusion can be made for fixed demand.
- For each instance, the local search algorithm can present an efficient vehicle routing schedule.
- The algorithm runs fast.

We specify another model where fairness is not considered. That means the first objective in VRM is ignored, and we specify this model as VRM'. The aim of proposing this model is to compare with VRM. Firstly, given three problems which information is shown in Table 7. Table

Problem No.		
1	deadline	77,61,60,66,49,67,73,41,82,81,75,64,45,82,50,63
	demand	1,8,22,21,9,23,12,15,16,17,16,18,13,18,13,16
	total demand	238
	total supply	200
2	deadline	89,82,56,70,47,53,81,74,41,69,63,86,55,44,64,90
	demand	24,15,17,20,3,1,14,1,12,5,20,16,1,23,20,23
	total demand	215
	total supply	200
3	deadline	78,60,57,66,69,79,79,65,81,64,51,69,74,74,88,79
	demand	19,22,25,13,16,20,12,14,5,4,6,3,4,12,20,8
	total demand	203
	total supply	200

Table 7. Problem information

8 shows the comparison between the solutions obtained from the above two models. When the total unsatisfied demand is big as that of problem 1, the unsatisfied rate, obtained from VRMąŕ, may be worse even though its total weighted time delay is smaller than that of VRM. While total unsatisfied demand is small, the VRM can present better solution than VRM', such as problem 3. A sample vehicle routing scheme when information is confirmed. Each type of line is corresponding to one vehicle route. For example, one vehicle drives from airport to hospital 8, 13, 6, 9 according to the red line. With different data input we have simulated cases

Problem No.	maximum unsatisfied demand		total weighted time delay		maximum unsatisfied rate	
	VRM	VRM'	VRM	VRM'	VRM	VRM'
1	38	38	325	435	0.1875	1
2	15	15	343	304	0.1	0.625
3	3	3	46	46	0.05	0.15

Table 8. Comparison between the above two models

of severe supply shortage, tight deadline, large fleet, and large number of randomly generated demand nodes. All these results show that the polynomial time algorithm is very efficient and can be a very useful tool in routing vehicles during a large-scale emergency scenario.

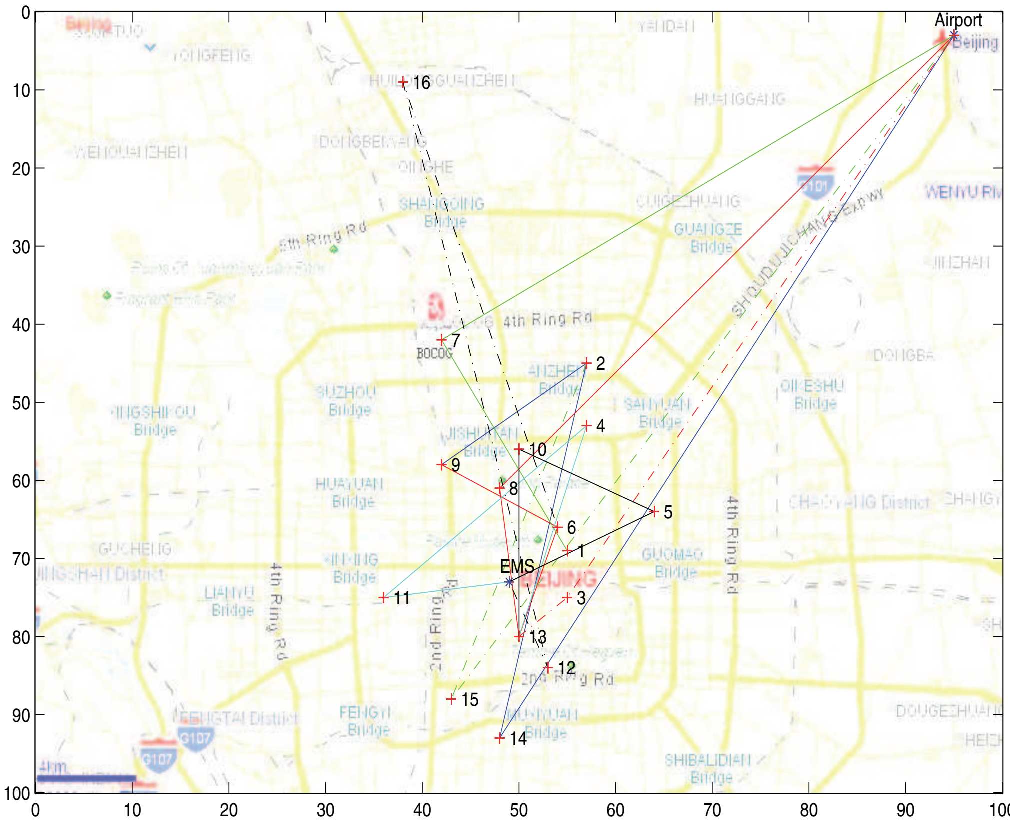

Fig. 2. Example for vehicles routing scheme

6. Conclusion

In this paper, we consider the vehicle routing problem under an emergency situation. A multi-objective model is formulated. Supplies may arrive with time delay, and the first objective is to minimize the total delay. We also consider fairness among demand nodes with respect to their unsatisfied rates. A new model and local search algorithm are presented. Simulation results show that the algorithm can be very useful for emergency responder to effectively use the available vehicles in case of emergencies.

For future work, we are going to design new algorithms for this model by using some other technique, such as heuristic algorithms. We will also try to formulate new models, when information about the demand and deadline are uncertain.

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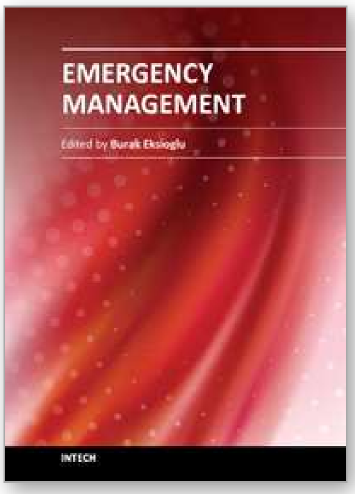

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After the large-scale disasters that we have witnessed in the recent past, it has become apparent that complex and coordinated emergency management systems are required for efficient and effective relief efforts. Such management systems can only be developed by involving many scientists and practitioners from multiple fields. Thus, this book on emergency management discusses various issues, such as the impact of human behavior, development of hardware and software architectures, cyber security concerns, dynamic process of guiding evacuees and routing vehicles, supply allocation, and vehicle routing problems in preparing for, and responding to large scale emergencies. The book is designed to be useful to students, researchers and engineers in all academic areas, but particularly for those in the fields of computer science, operations research, and human factor. We also hope that this book will become a useful reference for practitioners.

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