

Emergency Operations Scheduling for a Blood Supply Network in Disaster Reliefs

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Abstract: Emergency blood supply plays an important role in disaster relief. However, large fluctuations in blood demand make precise blood forecasting a challenge. The demand for blood and information about transportation disruption are dynamically revealed over time. A discrete-time Mixed Integer Linear Programming (MILP) mathematical formulation will be developed to cope with the underlying uncertainty through a rolling horizon approach with the purpose to optimally manage the blood supply chain system in disaster relief (i.e., determining the amount of blood collection, location of the blood collection stations, transport and storage needed to meet the demand in the worst-case scenario and minimize the total response time and total operational costs). The model also takes blood characteristics and blood emergency supply constraints into consideration. The performance of the proposed model and solution method is then investigated in a real case study from the 2008 Wenchuan earthquake and the results are discussed in detail. Copyright © 2019 IFAC

Keywords: emergency; blood supply network; disaster relief; rolling horizon

1. INTRODUCTION

Blood transfusion, which is significant in saving lives, is a key step in disaster relief. However, the information about numbers and types of wounds is unknown at the *early stage* (defined as the first 72 hours after the occurrence of a disaster, which is also called the *crucial period*) of disaster response, which results in difficulties in predicting the demand for blood. While the emergency blood relief starts as soon as a disaster occurs, decision-makers can only make a decision on blood operation based on their experience of disaster evaluation, which may not always be effective. For example, in the disaster relief for the 2008 Wenchuan earthquake in China, there was significant blood wastage caused by excessive and unbalanced types of blood collection and ineffective blood transport. The blood wastage was ten times more than that in normal blood banks.

The aforementioned facts highlight the need for an effective emergency blood supply network in disaster relief. The challenge of collecting enough blood and delivering the blood to the affected people in time falls within the scope of humanitarian aid supply chain management (Wassenhove, 2006), which is referred to as the disaster supply chain (DSC) (Syahrir et al., 2015) recently. The studies that address logistics operations for humanitarian disaster operations have been extensive in the past 20 years. But still, few have focused on the role of health care and the disaster supply chain (HDSC) (Syahrir et al., 2015). The authors who set up mathematical models and provide heuristic solutions to the DSC include De Angelis (2007), Chiu and Zheng (2007), Sheu (2007, 2010) and Taviana et al. (2018).

Given the fact that blood is not an ordinary commodity, it is necessary to review the supply chain management of blood components (BSC management). The readers are referred to

Beliën and Forcé (2012) and Osorio, et al. (2015) for detailed surveys. According to Beliën and Forcé (2012), modeling efforts that focus on strategic design of blood supply networks are scarce. Only six papers were found that applied the integer programming mathematical models to deal with blood transportation and/or location-allocation decision problems (Beliën and Forcé, 2012). In the above cited paper, the response to disaster has not been considered.

The five most recent and relevant papers in emergency blood supply chain network design were published by Sha and Huang (2012), Jabbarzadeh et al. (2014), Fahimnia (2017), Kouchaksaraei et al. (2018) and Samani et al. (2018). It is noticed that in the above five papers, either the blood characteristics have not been addressed or the disaster response time has not been considered as the first priority in making the emergency blood supply decision. This finding motivated the research for this paper. This paper contributes to the design of emergency blood supply chain networks for disaster relief in the following three ways: 1) A discrete-time Mixed Integer

Linear Programming (MILP) mathematical formulation is developed for this BSCP in disaster relief. The model takes both the blood characteristics (multi-blood types, blood compatibility, blood perishability) and emergency supply requirements into consideration (multi-transportation mode and minimize the response time). 2) The 2008 Wenchuan earthquake provides a realistic blood supply chain network in disaster relief, which incorporates blood centers in both the affected area and unaffected area, blood banks in the affected area, and hospitals in the affected area. 3) A rolling horizon implementation strategy is applied to find the solution for the MILP model. Rolling horizon has been applied largely in production planning and normal blood supply chain management problems. To our best knowledge, this is the

first time that the rolling horizon technique has been adopted for the BSCP in disaster relief.

The rest of the paper is organized as follows. In Section 2, a detailed description of the emergency blood supply network design problem is provided, and a mathematical model is set up for this problem. To find approximate solutions to large-scale emergency blood supply network design problems, a rolling horizon implementation strategy is presented in Section 3. Then in Section 4, a real case study of the 2008 Wenchuan earthquake is presented and a number of numerical results are shown to validate the proposed mathematical model and the algorithm. Finally, in Section 5, conclusions are drawn and future research directions are identified.

2. PROBLEM MODELLING

This section describes the emergency blood supply network design in disaster relief, its mathematical formulation, and a weighted sum scheme to convert the multi-objective model into a single-objective optimization model.

2.1 Problem description

In an emergency blood supply network, the strategic decision needs to be made. The organizational structure of an emergency blood supply network is shown in Figure 1. There are S blood centers, which supply blood from unaffected areas in a disaster to the blood center and blood banks in the affected area. There is only one blood center in one province in China. In the affected area, the blood center supplies blood to N blood banks in different cities in the affected area. There is only one blood bank in each city, which supplies blood to several hospitals in the city (i.e. blood bank 2 supplies blood to M hospitals). Blood collection can be in both blood centers and blood banks, but not hospitals.

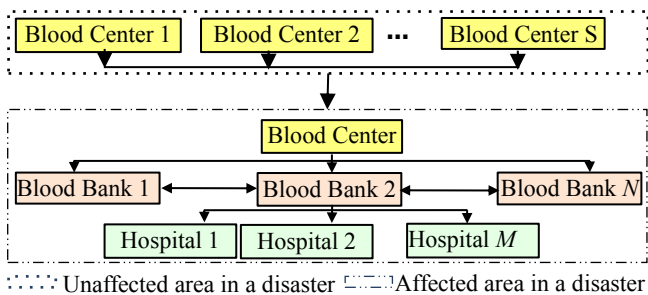


Figure 1 Organizational structure of an emergency blood supply network after an Earthquake disaster

In general terms, rescue efforts are made in a hierarchical system with a relatively small number of blood centers at the top level, a large number of hospitals at the bottom level and several blood banks at the middle level. Once a disaster takes place, blood orders flow from local hospitals to the involved blood banks and then converge to the blood center.

As a critical resource for life-saving operations, blood orders are highly sensitive to time. Therefore, before the blood orders arrive, the blood center should immediately predict the demand in order to collect blood with the limited information about the past or ongoing disaster using the software of the

Platform of National Emergency Response Center, which is supported by the forecasted demand theory.

From the blood center point of view, the combination of the two stages of forecast and scheduling could shorten the emergency blood dispatch time. Therefore, the actual demand for blood could be satisfied via the following four methods: 1) blood collection and inventory in the S blood centers in the unaffected area and blood transport from the S blood centers in the unaffected area to the blood center and blood banks in the affected area; 2) blood inventory of both blood centers and blood banks in the affected area; 3) blood collection in both blood centers and blood banks in the affected area; and 4) blood transport between the N blood banks and the blood center in the affected area mutually.

Some characteristics of the emergency blood supply planning problem in this paper are stated as follows:

1) Multi-period and bidirectional network. In Figure 1, if we take the blood centers and blood banks (both in affected areas and unaffected areas) as nodes $c_i, i = 1, \dots, n$, where n is the total number of nodes, and take the transportation routes as arcs, let $P = \{c_1, \dots, c_n\}$ be a node-set and $E = \{(c_i, c_j) | c_i, c_j \in P\}$ be an arc-set. Figure 1 can be regarded as a directed graph $G(P, E)$. Unlike the general supplier \rightarrow manufacturer \rightarrow distributor \rightarrow retailer \rightarrow customers one-way commercial supply chain, emergency blood supply planning needs to establish a bidirectional supply network in the affected area, in which demand nodes and supply nodes are time-varying. This is due to the fact that the demand for blood is time-varying in disaster events. Correspondingly, decision-making is time dependent. In reality, this dynamic blood dispatching procedure is dealt with over a multi-period horizon.

2) Blood characteristics. According to the Chengdu Blood Center, the red blood cells (RBC) are the most needed blood component during the quick response phase of a disaster (especially the first 24 hours). Thus we refer our blood component to RBCs only in the rest of this paper. Also, we use the word ‘blood’ to refer to the RBCs for simplicity. Given the fact that RBCs could be preserved for up to 35 days in 1–6 °C using Citrate Phosphate Dextrose Adenine (CPD-A1) bags, the collection and storage of blood requires specific conditions that directly affect the quality of the blood and blood transfusion safety. In particular, in the blood transportation process, transport time, temperature and other factors can cause a certain percentage of the blood transit loss. We define the *blood transportation discard rate*, which is a fractional value between $[0, 1]$ to measure the amount of blood discarded due to expiry during the blood transportation. Finally, a ‘first-in-first-out’ (FIFO) strategy is adopted, which means the blood nearest to the end of its shelf life is used first. Based on the above facts, an assumption is made that the blood delivered to the wounded is within its shelf life in disaster reliefs, thus blood shelf life constraint is implicitly considered in the blood transportation discard rate.

3) Constraints on the waiting time for blood. In emergency conditions, blood needs to be delivered to the wounded within the requested time limit to avoid loss of life. Each blood bank and blood center in the affected area will estimate the maximum waiting time for the blood to be delivered to them based on the storage on the inventory of blood available

for patient use in the hospitals that they cover at the beginning of the period. And the amount of the blood should be delivered to the affected blood banks and blood center in the affected area within the given waiting time limit.

4) Constraints on the ratio of blood types. There are four main types of blood: A, B, O and AB. Each type can be either RhD positive or RhD negative. Since in China the ratio of RhD negative blood to RhD positive blood is very low (1:99), the RhD positive/negative classification will not be applied in this mathematical model. In disaster relief, the four blood types mentioned above are collected, packaged and delivered in consistent with the ratio of blood type A, B, O and AB for Asian people. Since the ratio of blood types vary in different affected areas, upper and lower bounds of the percentage that each blood type is needed are defined to realize the blood type constraint for different blood banks. These upper and lower bounds are provided by the hospitals, which take the blood substitution into consideration.

5) Node failure. The blood bank facilities and equipment may be unaffected, partially damaged or completely damaged in the disaster. The partially damaged blood banks need to be repaired before they regain normal blood supply capabilities. The completely damaged blood banks lose both blood collection and supply capabilities. Node failure within a certain period of time will lead to the blood supply limitation or interruption, thus the maximum numbers of units of the blood of certain types that can be collected in different periods are different.

6) Arc failure. The relief blood can be transported by ambulance and airplane in emergency. The occurrence of an unexpected disaster may cause varying degrees of damage to the transportation infrastructure, including highways and airports, and other road resistance situations. As a result, some of the blood supply routes are interrupted and the transportation time, cost and blood transportation discard rate by different transportation mode could vary in different time periods, in which the transportation cost and blood transportation discard rate by different transportation mode are the functions of transportation time, which we could incorporate in our future work.

7) Bi-objectives. Disaster relief operations are time-critical because delays in the delivery of blood can cause increased suffering and perhaps death. Thus, the first objective in this study is to minimize the total time for blood collection center setup, blood collection and blood transportation. Although these activities could be done in parallel (i.e. blood center 1 does not have to wait for blood center 2 to set up), the loss of time in each activity will cause suffering in the same way. The second objective in this study is to minimize the total cost of blood collection center setup, blood collection and blood transportation. This objective has been frequently used in the literature. The bi-objective problem is converted into single objective optimization problem using a weighted sum scheme in Section 2.5.

Based on the above analysis, this paper proposes a bi-objective, multi-period, multi-blood type, multi-modal transportation MILP model to help decision makers to determine the amount of blood to collect in each period at each blood center/blood bank, the blood dispatching strategy at each blood center/blood bank and the blood level in the

inventory of each blood bank/center, with the objective to minimize the total time and cost for blood collection center setup, blood collection and blood transportation in the event of disaster. The MILP will be used within a rolling horizon scheme that periodically updates input data information.

2.2 Problem Assumptions

The following assumptions underlie this model:

- Information about the blood inventory, storage location and storage temperature can be tracked within the emergency distribution network. All the required data will be available on a daily basis.
- The collection teams will follow the collection goals (amount of blood of certain type to be collected in each period) obtained from the optimization model.
- Blood delivered to the wounded is within its shelf life in the crucial period (first 72 hours) of the disaster relief.
- The blood volume is considered as ml, rather than number of units (200 ml/unit), because of the difference of national standard in different countries. Thus the corresponding decision variables are fractional values.

2.3 Notations and Variables

In order to facilitate our explanation, the following notations will be used throughout this paper.

Notations

- | | |
|-----------------------|---|
| t | the identifier of the period indexed from 1 to T , where T is the number of periods. |
| A | set of blood types, indexed by blood type $a \in A$. |
| V | set of transportation modes, indexed by $v \in V$. |
| P | set of all blood banks and the blood centers in the affected area and all the blood centers in the unaffected area, indexed by $o, p \in P$. |
| P^A | set of all blood banks and the blood centers in the affected area only, indexed by $p \in P^A$. |
| I_{ap0} | Initial inventory of blood type a at node p immediately after the Earthquake. |
| \tilde{d}_{apt} | forecasted worst-case scenario demand of blood type a at node p in period t . |
| \tilde{C}_{appt} | estimated blood storage capacity of node p in period t . |
| \tilde{D}_{apt} | estimated maximum amount of blood type a that can be collected at node p in period t . |
| $\tilde{\xi}_{opvt}$ | estimated transportation time for dispatching blood by transportation mode v via arc (o, p) in period t . |
| \tilde{R}_{opvt} | estimated blood transportation discard rate by transportation mode v via arc (o, p) in period t . |
| $\tilde{\tau}_{opvt}$ | estimated unit transport cost by transportation mode v via arc (o, p) in period t . |
| $\tilde{\phi}_{pt}$ | estimated waiting time limit for the blood of all types to be delivered to node p in the current period $t = 1$. This waiting time is estimated based on the initial inventory I_{ap0} and the forecasted demand \tilde{d}_{ap1} . |
| η_p | set up time for blood collection at node p . |
| π_p | set up cost for blood collection at node p . |

- σ_{ap} unit blood collection time, which includes the donor blood collection time, blood fractionation and testing time for blood type a at node p .
- μ_{ap} unit blood collection cost for blood type a at node p .
- h_{ap} unit holding cost for blood type a at node p for one period.
- α_{ap} lower bound on the percentage of blood type a at node p .
- β_{ap} upper bound on the percentage of blood type a at node p .

Decision Variables

Z_{apt} : amount of blood type a collected at node p in period t .

X_{aopvt} : amount of blood type a dispatched by transportation mode v via arc (o, p) in period t .

I_{apt} : amount of blood type a at node p at the end of period t in inventory.

Y_{opvt} : is $\begin{cases} 1, & \text{if using transport mode } v \text{ on arc } (o, p) \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$

K_{pt} : is $\begin{cases} 1, & \text{if blood is collected at node } p \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$

2.4 Planning model

The objective function:

$$\text{Min } f_1 = \text{Min} \sum_{t=1}^T \sum_{p \in P} \left(\eta_p K_{pt} + \sum_{a \in A} \sigma_{ap} Z_{apt} + \sum_{o \in P} \sum_{v \in V} \xi_{opvt} Y_{opvt} \right) \quad (1)$$

$$\text{Min } f_2 = \text{Min} \sum_{t=1}^T \sum_{p \in P} \left[\sum_{a \in A} \left(h_{ap} I_{apt} + \sum_{o \in P} \sum_{v \in V} \tilde{\tau}_{opvt} X_{aopvt} + \mu_{ap} Z_{apt} \right) + \pi_p K_{pt} \right] \quad (2)$$

subject to

$$I_{apt} = I_{ap(t-1)} + \sum_{o \in P} \sum_{q \in P} \sum_{v \in V} [(1 - \tilde{R}_{opvt}) X_{aopvt} - X_{apqvt}] + Z_{apt} - \tilde{d}_{apt}, \forall a \in A, p \in P, t \in T \quad (3)$$

$$\sum_{q \in P} \sum_{v \in V} X_{apqvt} \leq I_{ap(t-1)}, \forall a \in A, p \in P, t \in T \quad (4)$$

$$\sum_{a \in A} I_{apt} \leq \tilde{C} \bar{\alpha}_{pt}, \quad \forall a \in A, p \in P, t \in T \quad (5)$$

$$Z_{apt} \leq \tilde{D}_{apt}, \forall p \in P, t \in T \quad (6)$$

$$(\tilde{\xi}_{opvt} - \tilde{\varphi}_{pt}) Y_{opvt} \leq 0, \forall o, p \in P, v \in V, t = 1 \quad (7)$$

$$\alpha_{ap} \leq \frac{Z_{apt}}{\sum_{a' \in A} Z_{a'pt}} \leq \beta_{ap}, \forall a \in A, p \in P, t \in T \quad (8)$$

$$\alpha_{ap} \leq \frac{X_{apqvt}}{\sum_{a' \in A} X_{a'pqvt}} \leq \beta_{ap}, \forall a \in A, p, q \in P, v \in V, t \in T \quad (9)$$

$$\sum_{a \in A} X_{aopvt} \leq M \cdot Y_{opvt}, \forall o, p \in P, v \in V, t \in T \quad (10)$$

$$\sum_{a \in A} Z_{apt} \leq M \cdot K_{pt}, \forall p \in P, t \in T \quad (11)$$

$$X_{aopvt}, I_{apt}, Z_{apt} \geq 0, Y_{opvt}, K_{pt} = 0 \text{ or } 1, \forall a \in A, \forall o, p \in P, v \in V, t \in T \quad (12)$$

In the above mathematical model, objective function (1) represents the total time to be minimized, which consists of setup time for blood collection, blood collection time and blood dispatching time. Objective function (2) represents the total cost to be minimized, which consists of blood equipment setup cost, blood holding cost, blood dispatching cost and blood collecting cost, where blood collecting cost includes blood processing and testing costs. The constraint (3) represents the balance between supply and demand for RBCs. The constraint (4) guarantees that the amount of blood dispatched in period t should not exceed the amount of blood in the inventory at the end of period $t - 1$. The constraint (5) guarantees that the amount of blood in the inventory will not exceed the capacity of the blood center or the blood bank. The constraint (6) guarantees that the amount of blood collected in period t will not exceed the blood supply capacity in that period. The constraint (7) guarantees that the blood dispatching time does not exceed the upper bound of the waiting time limit in the first period. The constraint (8) represents that the frequency of blood type a obtained through blood collection should be within its lower and upper bounds. The constraint (9) represents that the frequency of blood type a obtained through blood transportation should be within its lower and upper bounds. The constraints (10) and (11) validate the definition of the binary variables, where M is a large number. The constraint (12) describes the decision variable domain.

2.5 Multi-Objective Method

A comprehensive survey of the multi-objective optimization methods is presented in the literature by Ruzica and Wiecek (2005). As the weighted sum method is the simplest approach and probably the most widely used classical method (Narzisi, 2008), this paper adopts the weighted sum method. To apply this method, the coefficient λ_t to convert time value into cost value is introduced firstly to evaluate two objectives using the fair value measurement. Secondly, we define the time and cost weighting coefficients θ_1 and θ_2 respectively, where $\theta_1 + \theta_2 = 1$. Different combinations of θ_1 and θ_2 can be used in different relief periods. For example, in the early stage (first 72 hours) of relief, we have $\theta_1 > \theta_2$. A sensitivity analysis with different combinations of θ_1 and θ_2 is provided in Section 3 Case Study. The problem is now converted to a single objective mixed integer linear programming (MILP); the objective function is as follows:

$$\text{Min } f = \theta_1 \sum_{t=1}^T \lambda_t \sum_{p \in P} (\eta_p K_{pt} + \sum_{a \in A} \sigma_{ap} Z_{apt} + \sum_{o \in P} \sum_{v \in V} \xi_{opvt} Y_{opvt}) + \theta_2 \sum_{t=1}^T \sum_{p \in P} [\sum_{a \in A} (h_{ap} I_{apt} + \sum_{o \in P} \sum_{v \in V} \tilde{\tau}_{opvt} X_{aopvt} + \mu_{ap} Z_{apt}) + \pi_p K_{pt}] \quad (13)$$

2.6 Rolling horizon framework

The approaches to cope with scheduling and planning problem with uncertainties include reactive and proactive approaches. The proactive approaches are based on the consideration of all possible scenarios with their associated probabilities and finding good solutions for all these scenarios. These approaches include stochastic programming and robust optimization, which count on accurate estimations of the probabilities of the scenarios. In this paper, a reactive approach called rolling horizon is applied, which focuses on setting the strategic targets for the sub-horizon obtained by solving the proposed MILP model in the previous section, and updating the input data of the MILP for the following sub-horizon with the current detailed operational results. The rolling horizon framework allows decision makers to make use of data that is revealed as time progresses.

Generally, discrete time representation is used for the whole planning time domain H , and the length of a sub-horizon has been indicated in Section 2.3 as T . A schematic diagram for input/output flows of the implementation of the rolling horizon is given in Figure 2, in which $H = 5$, $T = 3$ and $p_i, i = 1 \dots 5$ are the five periods in the planning time domain H .

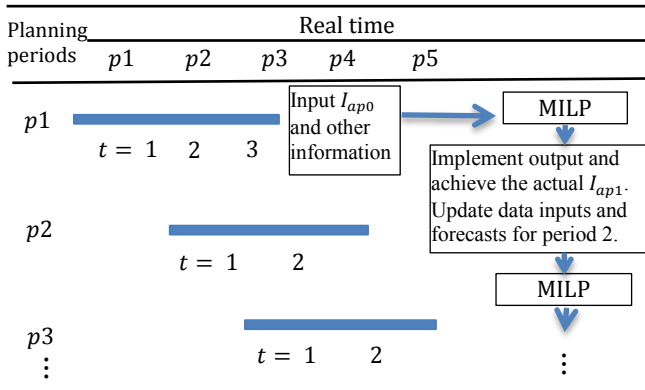


Figure 2 A schematic diagram for input/output flows of the implementation of the rolling horizon

The rolling horizon framework has been widely applied in production planning problems (Sahin, 2013). It has also been applied to both BSC problems (Osorio, 2017) and DSC problems (Lu et al., 2016). To our best knowledge, this is the first time that the rolling horizon framework has been applied to the blood supply and dispatch planning problem for a disaster relief.

3. CASE STUDY AND NUMERICAL RESULTS

To evaluate the mathematical model developed in this paper, the 2008 earthquake in Wenchuan, China, has been investigated. The case is described in detail, and the data input for the Wenchuan 2008 earthquake was simulated. Then the results by FICO Xpress Workbench Version 2.1.4 are provided with a number of sensitivity analyses.

Authorized by the Health Department of Sichuan Province, the Chengdu Blood Center is responsible for emergency blood deployment, dispatching most of the blood from unaffected provinces A and B to blood centers in affected areas C, D, E, F in the disaster; ‘National Blood-Dispatch

Nodes’ are blood centers and ‘Blood-Dispatch Nodes in Sichuan Province’ are blood banks.

The forecasted demands in worst-case scenario \tilde{d}_{apt} are listed in Table 1. This case study concerns the first six days of the earthquake, when the demand for RBCs is great. So the product in this emergency blood supply planning problem is the RBC suspension (with a shelf life of 35 days), which contains four blood types: A(I), B(II), O(III) and AB(IV) ($|A| = 4$). There are two transportation modes ($|V| = 2$) in total to consider in this case study: airplane or ambulance. Nodes A and B are pure supply points outside the disaster areas, thus there is no demand for blood from nodes A and B. Due to the size of the paper, the rest of the input data will not be given.

Table 1. The forecasted demand in worst-case scenario d_{apt} ($\times 1000$ ml)

T	A				B				C			
	I	II	III	IV	I	II	III	IV	I	II	III	IV
1	0	0	0	0	0	0	0	0	210	200	230	60
2	0	0	0	0	0	0	0	0	330	300	360	110
3	0	0	0	0	0	0	0	0	140	120	150	50
4	0	0	0	0	0	0	0	0	140	130	140	50
5	0	0	0	0	0	0	0	0	260	250	330	100
6	0	0	0	0	0	0	0	0	200	220	260	80

t	D				E				F			
	I	II	III	IV	I	II	III	IV	I	II	III	IV
1	70	45	75	20	120	100	140	40	50	40	50	20
2	190	170	200	60	80	80	90	30	25	20	30	5
3	15	10	20	5	55	50	60	15	150	120	170	40
4	60	60	60	20	35	30	45	10	15	15	15	5
5	60	50	75	15	30	30	30	10	25	20	25	10
6	130	120	150	50	70	60	65	25	40	40	50	20

The mathematical model in Section 2.4 and 2.5 is coded with FICO Xpress Workbench Version 2.1.4 on an Intel Core 2 Duo CPU 1.70GHz 2.40 GHz. In this experiments, $\lambda_t = 1000$ RMB/hour is defined for $t = 1 \dots 6$ by the decision maker of the blood center. The numerical results for a set of combinations of weight coefficients of time and cost (θ_1 and θ_2), respectively, are provided in Table 2, where f_1 and f_2 are total time and total cost obtained using FICO Xpress Workbench Version 2.1.4 optimization software, which are optimal objective function values. As explained in Section 3.5, time factors have the priority over cost factors. Table 2 only provides the combinations of θ_1 and θ_2 with the values $\theta_1 > \theta_2$.

Table 2. Numerical result for the case study with different combinations of θ_1 and θ_2

θ_1	θ_2	f_1 (hours)	f_2 (RMB)
0.6	0.4	3102.48	4,173,870
0.7	0.3	3098.22	4,182,130
0.8	0.2	3087.60	4,213,610
0.9	0.1	3076.02	4,290,440

From Table 2, it is note that by varying the weights of the times and costs, a number of distinctive solutions can be found for the decision maker to choose from, so as to respond the disaster quickly.

Figure 3 gives an example solution with $\theta_1 = 0.9$ and $\theta_2 = 0.1$ for the situation that node D and F are located in partially damaged area and full blood supply capacity and storage capacity can only be achieved by peirod 6. Also the transportation time could be delayed in the node D due to the damage.

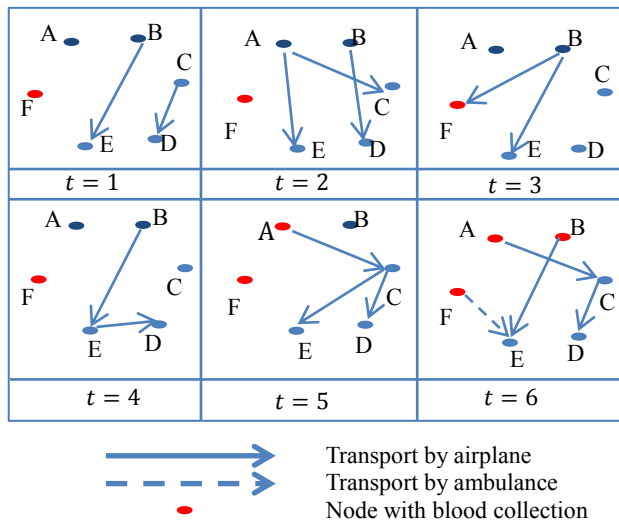


Figure 3 Example solution

4. CONCLUSION

The demand for blood is very difficult to forecast after disasters, thus the excessive blood collection and unscheduled blood dispatching always lead to a huge amount of blood waste due to the fact that blood is a perishable product. In the literature on the emergency blood scheduling research area, no rolling horizon implementaion strategy has been applied to the problem investigated in this paper. Thus, in this study, a multi-period mathematical model with multi-type RBCs and multi-modal transport is set up. The implementation of rolling horizon strategy is discussed. The simulation results and sensitivity analysis of the case of the 2008 Wenchuan earthquake has indicated the practicality of the model.

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