Chapter 6
Integrated Optimization Model for Two-Level Epidemic-Logistics Network

As mentioned in the above chapters, the demand of emergency resource is usually uncertain and varies quickly in anti-bioterrorism system. With the consideration of emergency resources allocated to the epidemic areas in the early rescue cycles will affect the demand in the following periods, we construct an integrated and dynamic optimization model with time-varying demand for the emergency logistics network based on the epidemic diffusion rule. The heuristic algorithm coupled with 'DDE23 tool' in MATLAB is adopted to solve the optimization model, and the application of the model as well as a short sensitivity analysis of the key parameters in the time-varying demand forecast model is presented by a numerical example. The win-win emergency rescue effect is achieved by such an optimization model. Thus, it can provides some guidelines for decision makers when coping with emergency rescue problem with uncertain demand, and offers an excellent reference when issues are pertinent to bioterrorism.

6.1 Introduction

Bioterrorism is the intentional use of harmful biological substances or germs to cause widespread illness and fear. It is designed to cause immediate damage and release dangerous substances into the air and surrounding environment. Because it would not usually be signaled by an explosion or other obvious cause, a biological attack may not be recognized immediately and may take local health care workers time to discover that a disease is spreading in a particular area.

Over the past few years, the world has grown increasingly concerned about the threat bioterrorists pose to the societies, especially after the September 11 attacks and the fatal delivery of anthrax via the US Mail in 2001. Henderson [1] points out that the two most feared biological agents in a terrorist attack are smallpox and anthrax. Radosavljević and Jakovljević [2] propose that biological attacks can cause an epidemic of infectious disease, thus, epidemiological triangle chain models can be used to present these types of epidemic. Bouzianas [3] presents that the

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deliberate dissemination of *Bacillus anthracis* spores via the US mail system in 2001 confirm their potential use as a biological weapon for mass human casualties. This dramatically highlights the need for specific medical countermeasures to enable the authorities to protect individuals from a future bioterrorism attack.

Generally, emergency logistics in anti-bioterrorism system is more complex and difficult, and differs from business logistics in the following aspects. First of all, a bioterror attack usually happens suddenly and causes a surge of demand for a particular medicine during a very short period of time. Hence, emergency resources must be allocated to the epidemic areas as quickly as possible. Second, the demand information is quite limited and varies rapidly with time. It is often very difficult to predict the actual demand based on historical data [4]. Third, unlike logistics management in which all the activities are triggered based on customer orders, emergency logistics network in the anti-bioterrorism system is derived from the epidemic diffusion network.

Considering the relationship between an unexpected bioterror attack and the associated emergency logistics decisions, Liu and Zhao [5, 6] focus on how to control the emergency resources and divide the whole emergency rescue process into three stages. In the first stage, for the disaster area is just suffered from a bioterror attack, and the bio-virus (such as smallpox, Bacillus anthracis and so on) hasn't cause a widespread diffusion, thus, we should deliver the existing emergency resources in the local health departments to the disaster areas as quickly as possible. Then, objective of the second stage is that emergency resources can be allocated to the disaster areas along with the spreading of the bio-virus, continually. Thus in this study, we focus on the third rescue stage, and the following problem should be answered: how to replenish emergency resources to the local health departments, and simultaneously, how to allocate emergency resource to the infected areas? To accomplish such objective, we employ network flow techniques to develop an integrated and dynamic optimization model, with the objective of minimizing the total rescue cost and subject to related operating constraints. The model is expected to be an effective decision-making tool that can help improve the efficiency of emergency rescue when suffered from a bioterror attack.

6.2 Problem Description

As mentioned before, we have divided the entire emergency rescue process into three stages in Liu and Zhao [5], and this study focuses on the optimization of the emergency logistics network in the third rescue stage. In such stage, situation of the epidemic diffusion tends to be stable and the spread of the epidemic goes to under control. Thus, optimization goal in such stage is to construct an integrated, dynamic and multi-level emergency logistics network, which includes the national strategic storages, the urban health departments and the epidemic areas. The research idea of the third emergency rescue stage is shown in Fig. 6.1.

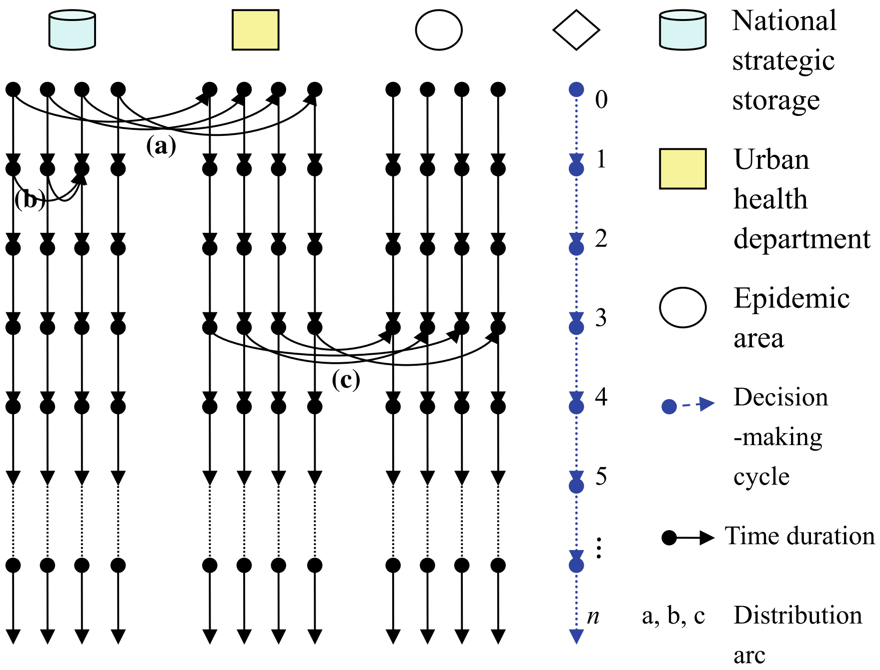

Fig. 6.1 Research idea of the third emergency rescue stage

As Fig. 6.1 shows, the entire rescue process in the third emergency rescue stage is decomposed into several mutually correlated sub-problems (i.e. n decision-making cycles). To each decision-making cycle, there exist two sub-problems. In the upper level, we consider the problem how to replenish emergency resources to the urban health departments. Besides, we adjust the replenishment arcs by a heuristic algorithm, and construct a mixed-collaborative delivery system. Thus, the total rescue cost of the upper level sub-problem would be minimized. In the lower level, we present the problem how to allocate emergency resources to the infected areas. We propose a forecasting model for the time-varying demand in the epidemic areas based on the epidemic diffusion rule. Such two phases are executed iteratively. Besides, at the end of each rescue cycle, effect of emergency resources allocated is analyzed and the number of infected people is updated. Such a sequential operational routine is continued until the bio-virus diffusion is under control.

It is worth mentioning that the optimal result of the upper level sub-problem affects the result of the lower level sub-problem, directly; on the other side, the optimal result of the lower level sub-problem will affect the result of the upper level sub-problem in the next emergency rescue cycle. Therefore, this is different to the bi-level programming method. In what follows, we will present the SEIR epidemic diffusion model and the forecasting models for the time-varying demand and inventory.

6.2.1 SEIR Epidemic Diffusion Model

Since most epidemics divide people into four classes: the susceptible people (S), the people during the incubation period (E), the infected people (I), and the recovered people (R). Thus, as Fig. 6.2 shows, without consideration of the population migration, and the natural birth and death rate of the population, we can use a SEIR model based on small-world network to describe the developing epidemic process.

Therefore, the following SEIR model [6] is adopted in this study.

$$\begin{cases} \frac{dS}{dt} = -\beta\langle k\rangle S(t)I(t) \\ \frac{dE}{dt} = \beta\langle k\rangle S(t)I(t) - \beta\langle k\rangle S(t-\tau)I(t-\tau) \\ \frac{dI}{dt} = \beta\langle k\rangle S(t-\tau)I(t-\tau) - (d+\delta)I(t) \\ \frac{dR}{dt} = \delta I(t) \end{cases} \tag{6.1}$$

In such epidemic diffusion model, the time-based parameters $S(t)$, $E(t)$, $I(t)$ and $R(t)$, represent the number of susceptible people, the number of people during the incubation period, the number of infected people, and the number of recovered people, respectively. Other parameters include: $\langle k\rangle$ is the average degree distribution of the small-world network; β is the propagation coefficient of the bio-virus (smallpox); δ is the recovered rate of the infected people; d is the death rate caused by the disease; τ stands for the incubation period. Furthermore, $\langle k\rangle, \beta, \delta, d, \tau > 0$.

From the Eq. (6.1), we can see that $I(t)$, which denotes the number of infected people, can be calculated by solving the ordinary differential equations when the initial values of $S(t)$, $E(t)$, $I(t)$ and $R(t)$ are given. Actually, this parameter is one of the most important concerns during the emergency rescue process, and it is desired that $I(t)$ stays at a value as low as possible, which implies that the situation is stable and the spread of the epidemic is under control. Wang et al. [4] propose that the change of $I(t)$ mainly depends on the population of the recovered people and the onset people at the end of the incubation period. And thus, we should improve the recovered rate δ and reduce the propagation coefficient β, thereby decreasing the value of $I(t)$ effectively.

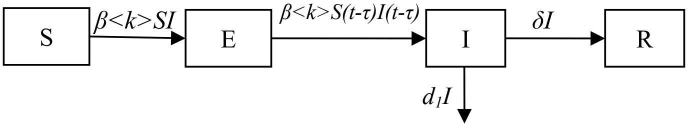

Fig. 6.2 SEIR epidemic diffusion model

6.2.2 *Forecasting Model for the Time-Varying Demand*

As mentioned before, for both upper and lower sub-problems are existed in each emergency rescue cycle, thus, the time-varying demand in each sub-problem should be the forecasted respectively.

(1) **Forecasting model for the time-varying demand in the epidemic area**

As introduced in Sect. 6.1, the demand information is quite limited and varies rapidly with time when suffered from a bioterror attack. Thus, it is often difficult to predict the actual demand based on historical data. Xu et al. [7] propose that demand forecasting after a disaster is especially important in emergency management, and present an EMD-ARIMA (empirical mode decomposition and autoregressive integrated moving average) forecasting methodology to predict the agricultural products demand after the 2008 Chinese winter storms. Other related works can be found in [8, 9]. Note that emergency demand in the previous literature has always been formulated as a stochastic or deterministic variable, while the effectiveness that emergency resource allocated in the early rescue cycle will affect the demand in the later rescue cycle has not been considered. Based on the previous works ([5]), the following forecasting model for the time-varying demand in the epidemic area is adopted in this study.

$$d_t^* = aI(t), \quad t \in 0, 1, 2, \ldots, n \tag{6.2}$$

$$\eta_t = {(d_{t+1}^* - d_t^*)}/{d_t^*}, \quad t \in 0, 1, 2, \ldots, n-1 \tag{6.3}$$

$$\text{When} \ \ t = 0, \quad d_0 = aI(0) \tag{6.4}$$

$$\text{When} \ \ t = 1, \quad d_1 = (1 + \eta_0)\left(1 - \frac{\theta}{\Gamma}\right)d_0 \tag{6.5}$$

$$\text{When} \ \ t = 2, \quad d_2 = (1 + \eta_1)\left(1 - \frac{\theta}{\Gamma}\right)d_1 = (1 + \eta_0)\left(1 + \eta_1)(1 - \frac{\theta}{\Gamma}\right)^2 d_0 \tag{6.6}$$

$$\ldots$$

$$\text{When} \ \ t = n, \quad d_n = \prod_{i=0}^{n-1}(1 + \eta_i)\left(1 - \frac{\theta}{\Gamma}\right)^n d_0 \tag{6.7}$$

Herein, $\prod_{i=0}^{n-1}(1 + \eta_i) = (1 + \eta_0)(1 + \eta_1)\ldots(1 + \eta_{n-1})$. Equation (6.2) is the traditional forecasting model for the time-varying demand. d_t^* means demand of the emergency resources in the epidemic area at time t, $t \in 0, 1, 2, \ldots, n$. $I(t)$ is the number of infected people in the epidemic area at time t. a is the proportionality coefficient. Equation (6.3) is used to calculate the linear scale factor of the change in demand for each rescue cycle. Furthermore, $\eta_t \leq 0$. d_0 in the Eq. (6.4) is the initial demand of emergency resources in the epidemic area, and $I(0)$ represents the initial number of infected people in the epidemic area. $d_1, d_2, \ldots, d_n$ in Eqs. (6.5)–(6.7) represent the demand of emergency resources in emergency rescue cycle $1, 2, \ldots, n$. Other parameter include: θ is the effective rescue rate in each cycle; Γ is the treatment cycle for each infected person. To facilitate the calculation process in the following sections, we assume that Γ is an integral multiple of the rescue cycle.

According to the above recursion formulas, the change of emergency demand mainly depends on these two important parameters. Thus, in the context of emergency rescue, there should be enough emergency resources to cure the infected people, so that the effective rescue rate θ can be improved and the treatment cycle $\mathit{\Gamma}$ can be reduced, thereby, decreasing the total emergency rescue cost.

(2) **Forecasting model for the time-varying demand in urban health department**

As introduced before, in the upper level sub-problem, we consider the problem how to replenish emergency resources to the urban health departments. Thus, the urban health departments, which are the emergency suppliers in the lower level sub-problem, have been changed to be the demand nodes in the upper level replenishment network. Note that time-varying demand in the urban health department mainly depends on the unsatisfied capacity. Hence, to facilitate the calculation process in the following sections, we assume that the initial inventory in each urban health department is equal to zero. Besides, we suppose that capacity of each urban health department is equal to V_{cap}. Supposing that d_t^v represents the demand of emergency resources in urban health department at rescue cycle t, P_t represents the total supply of the emergency resources in urban health department at rescue cycle t (Such value is obtained by solving the lower level sub-problem in the previous rescue cycle). Thus, the forecasting model for time-varying demand in urban health department can be formulated as follows.

$$d_t^v = \begin{cases} V_{cap}, & t = 0 \\ P_{t-1}, & t = 1, 2, \ldots, n \end{cases} \tag{6.8}$$

6.2.2.1 Forecasting Model for the Time-Varying Inventory

As mentioned in Sect. 6.1, the focus of this study is placed on replenishing emergency resources to the urban health departments and distributing them to the epidemic areas, simultaneously. Thus, the urban health departments play the role of the link in the multi-level emergency logistics network. Intuitively, inventory of the emergency resources in the urban health department should also be changed as time goes by. Supposing that V_t is the inventory of the emergency resources in the urban health department at rescue cycle t, and we can get the following equation.

$$V_t = \begin{cases} 0, & t = 0 \\ V_{cap} - P_{t-1}, & t = 1, 2, \ldots, n \end{cases} \tag{6.9}$$

6.3 Optimization Model and Solution Methodology

6.3.1 The Integrated Optimization Model

To facilitate the model formulation in the following section, we make the following four assumptions.

(1) Once suffered from a bioterror attack, each epidemic area can be isolated from other areas to avoid the spread of the disease.
(2) The locations of the national strategic storages, and urban health departments are known. Practically, the number of storage places to be used can be preset by a national disaster plan.
(3) Holding cost of the emergency resources is not considered.
(4) Capacity of the national strategic storage is large enough, and in each rescue cycle, each one of them can supply a certain amount of emergency resources.

Notations used in the following integrated and dynamic optimization model are specified as follows.

nc_{ij}: Unit replenishment cost of the emergency resource from the nation strategic storage i to the urban health department j.
ce_{jk}: Unit distribution cost of the emergency resource from the urban health department j to the epidemic area k.
ns_i: The certain amount of emergency resources that can be supplied by the nation strategic storage i in each rescue cycle.
V_{cap}: Capacity of the urban health department.
d_{kt}: Demand of the emergency resources in epidemic area k at rescue cycle t.
d^v_{jt}: Demand of the emergency resources in urban health department j at rescue cycle t.
P_{jt}: Total supply of the emergency resources in urban health department j at rescue cycle t.
V_{jt}: Inventory of the emergency resources in the urban health department j at rescue cycle t.
x_{ijt}: Amount of the emergency resources that transport from the national strategic storage i to the urban health department j at rescue cycle t.
y_{jkt}: Amount of the emergency resources that transport from the urban health department j to the epidemic area k at rescue cycle t.
TC: Total cost of the multi-level emergency logistics network.
N: Set of the national strategic storages.
C: Set of the urban health departments.

E: Set of the epidemic areas.
T: Set of the decision-making cycles.

According to the above explanation and assumptions, the integrated and dynamic optimization model for the multi-level emergency logistics network can be formulated as follows:

$$\text{Min } TC = \sum_{t\in T}\sum_{i\in N}\sum_{j\in C} x_{ijt}nc_{ij} + \sum_{t\in T}\sum_{j\in C}\sum_{k\in E} y_{jkt}ce_{jk} \tag{6.10}$$

$$\text{s.t.} \quad \sum_{j\in C} x_{ijt} \le ns_i, \quad \forall i \in N, \quad t \in T \tag{6.11}$$

$$\sum_{i\in N} x_{ijt} = d^v_{jt}, \quad \forall j \in C, \quad t \in T \tag{6.12}$$

$$d^v_{jt} = V_{cap}, \quad \forall j \in C, \quad t = 0 \tag{6.13}$$

$$d^v_{jt} = P_{jt-1}, \quad \forall j \in C, \quad t = 1, 2, \ldots, T \tag{6.14}$$

$$P_{jt} = \sum_{k\in E} y_{jkt}, \quad \forall j \in C, \quad t \in T \tag{6.15}$$

$$\sum_{k\in E} y_{jkt} \le V_{cap}, \quad \forall j \in C, \quad t \in T \tag{6.16}$$

$$\sum_{j\in C} y_{jkt} = d_{kt}, \quad \forall k \in E, t \in T \tag{6.17}$$

$$d_{kt} = aI_k(t), \quad \forall k \in E, \quad t = 0 \tag{6.18}$$

$$d_{kt} = \prod_{i=0}^{t-1}(1+\eta_{ki})\left(1-\frac{\theta}{\Gamma}\right)^t d_{k0}, \quad \forall k \in E, \quad t = 1, 2, \ldots, T \tag{6.19}$$

$$\prod_{i=0}^{t-1}(1+\eta_{ki}) = (1+\eta_{k0})(1+\eta_{k1})\ldots(1+\eta_{k(t-1)}), \forall k \in E, t = 1, 2, \ldots, T \tag{6.20}$$

$$x_{ijt} \ge 0, \quad \forall i \in N, \quad j \in C, \quad t \in T \tag{6.21}$$

$$y_{jkt} \ge 0, \quad \forall j \in C, \quad k \in E, \quad t \in T \tag{6.22}$$

Herein, the objective function in Eq. (6.10) is to minimize the total cost of the multi-level emergency logistics network. Equations (6.11) and (6.12) are constraints for flow conservation in the upper level sub-problem. Equations (6.13)–(6.15) are the time-varying demand models in the upper level sub-problem. Equations (6.16) and (6.17) are constraints for flow conservation in the lower level sub-problem. Equations (6.18)–(6.20) are the time-varying demand models in the lower level sub-problem. At last, Eqs. (6.21) and (6.22) ensure all the arc flows in the emergency logistics network within their bounds.

Our model is formulated as an integrated, dynamic and multi-stage programming model, and could thus be difficult to solve directly, especially for realistically large-scale problems. Therefore, as mentioned in Sect. 6.2, we should decompose the problem into several mutually correlated sub-problems, and then solve them systematically in the same decision scheme. In what follows, we will develop a heuristic algorithm to efficiently solve the problem.

6.3.2 Solution Methodology

(1) **Solution procedure for the optimization model**

As introduced before, we decompose the entire emergency process in the third rescue stage into n sub-problems (i.e. n decision-making cycles or n rescue cycles). Thus, to each rescue cycle, the research problem has been become a two correlated programming problems and simple to solve. The 'DDE23' tool in MATLAB coupled with the forecasting model for the time-varying demand (As introduced in Sect. 6.2.2) is adopted to calculate the dynamic demand. Then, the solution procedure can be presented as follows.

Step 1. Preset the decision-making cycle, and decompose the entire emergency process in the third rescue stage into n decision-making cycles.
Step 2. Let $t = 0$, and initialize parameters in the SEIR epidemic diffusion model.
Step 3. Analyze the epidemic diffusion rule, and calculate the initial demand of the emergency resources in each epidemic area according to the Eq. (6.18).
Step 4. Solve the two correlated programming problems in rescue cycle $t = 0$ and obtain the initial solution.
Step 5. Improve the initial solution by heuristic algorithm (Detail about the heuristic algorithm is introduced in Sect. 6.3.2).
Step 6. Get the final solution of the emergency allocation in such rescue cycle.
Step 7. Set $t = t + 1$, if the termination condition for the rescue cycle is not satisfied, update the demand in each epidemic area and urban health department, and update the inventory level of the emergency resources in each urban health department, go back to Step 3. Else, go to the next step.
Step 8. End the programme and output the final result.

(2) **Heuristic algorithm for improving the initial solution**

It is not difficult to find that only two types of distribution arcs (type (a) and (c) in Fig. 6.1) have been optimized in the above model, while the collaborative arcs (type (b) in Fig. 6.1) have not been considered. In other words, the collaborative effect among the national strategic storages has not been considered. Zhao and Sun [10] propose that emergency rescue system with a supply source can results in better performance in both aspects of operational efficiency and operating cost. Thus, to improve the performance of the emergency rescue system without supply source, as Fig. 6.3 shows, we can select an adjacent national strategic storage in the network as the HUB location, and then take the national strategic storages which are at some distance from the epidemic area as the supply sources. As a result, a mixed-collaborative replenishment system is constructed.

Obviously, such mixed-collaborative replenishment system allows both hub-and-spoke and direct shipment (we call it point to point mode) delivery modes. Thus, both advantages of the economies of scale in hub-and-spoke system and the effectiveness in direct shipment system can be taken account. It is worth mentioning that some previous works are related (e.g. [11, 12]), and the experiment results in these works show that the mixed system can save total traveling distance or delivery cost as compared with either of the two pure systems. Therefore, such mixed-collaborative system can improve the initial solution in the last section. Besides, the heuristic algorithm in Liu et al. [12] can be applied in this study with suitable modified as follows (The flowchart of the procedure is also given in the Fig. 6.4).

Step 1. Solve the pure point to point replenishment mode, and let the distribution arc set be D^d. By solving the objective Eq. (6.10), we can get the total emergency replenishment cost at rescue cycle *t*. Let $TC^d = \sum_{i \in N} \sum_{j \in C} x_{ijt} n c_{ij}$.
Step 2. Solve the pure hub-and-spoke problem. This is done as follows: select a national strategic storage $h (h \in N)$ which is adjacent to the epidemic areas as the HUB location, and then, solve a programming problem with the depot located at *h*

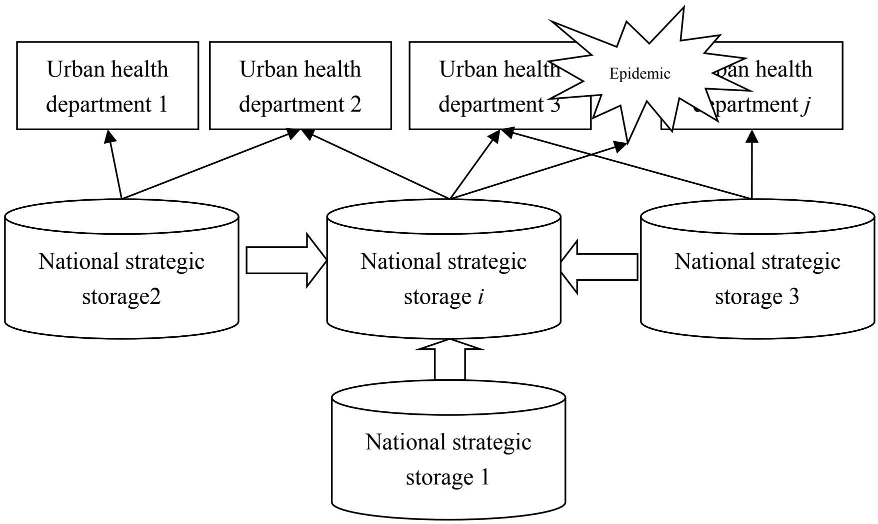

Fig. 6.3 Mixed-collaborative replenishment system

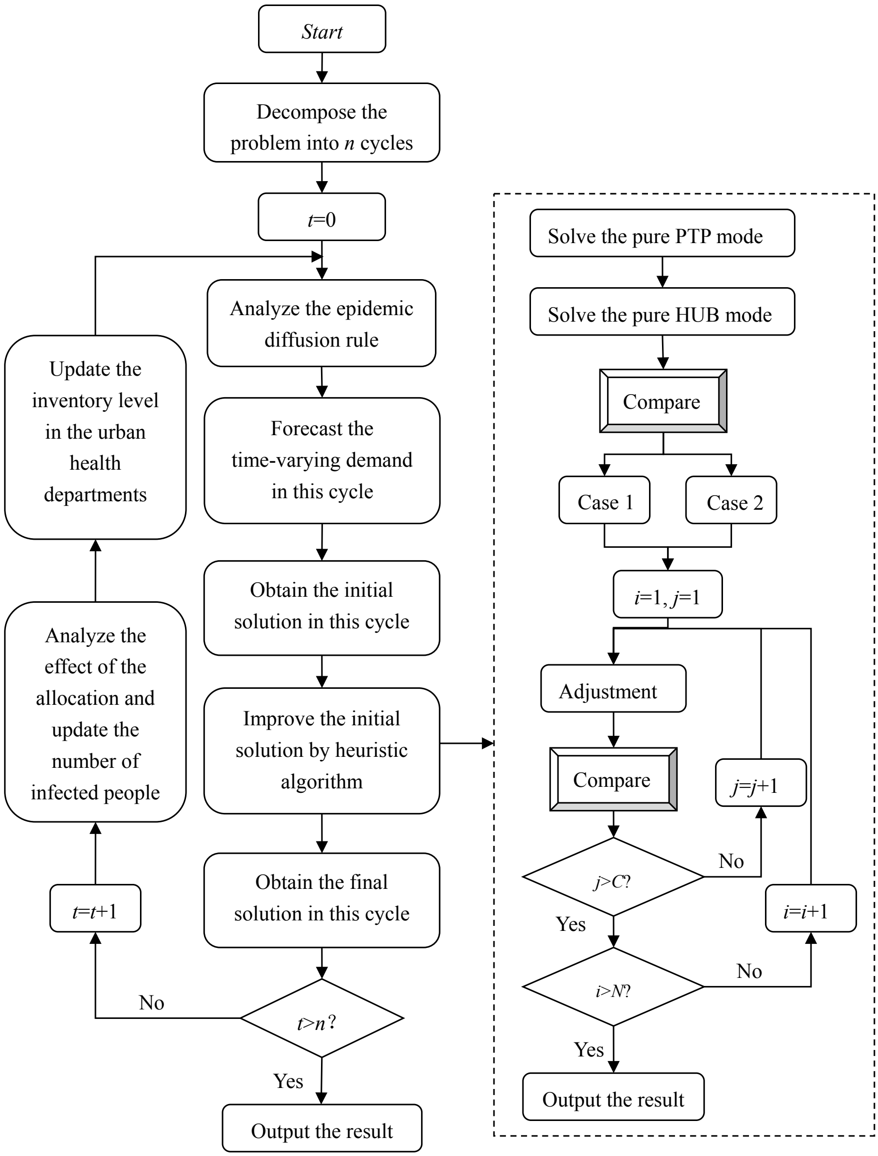

Fig. 6.4 The flowchart of the solution procedure

to collect the emergency resources from all the other storages and to distribute the emergency resources to the urban health departments. Let the distribution arc set be D^h. q_{ih} represents amount of emergency resources that transport from national strategic storage i to the HUB, and the unit transportation cost is nz_{ih}. Thus, $TC^h = \sum_{i \in N \backslash h} z_{ih} q_{ih} + \sum_{h \in N} \sum\limits_{j \in C} x_{hjt} nc_{hj}$ is the total emergency replenishment cost at rescue cycle t.

Step 3. Compare TC^d and TC^h, if $TC^d < TC^h$, let $D^d = D$, $D^h = \varnothing$, record it as the case 1; else if $TC^d \geq TC^h$, let $D^h = D$, $D^d = \varnothing$ and record it as the case 2. Let $TC^s = \min\{T^d, T^h\}$ and $TC^m \leftarrow TC^s$.

Step 4. Adjust the distribute arc according to the following two situations.

Step 4.1. If case 1 appears, then for every replenishment arc $(N_i, C_j) \in D^d$, compute S_{ij}^{dh}, which is an estimate of the improvement in the solution value if the replenishment arc is transferred from D^d to D^h. Transfer all those pairs with positive S_{ij}^{dh} from direct shipment delivery to hub-and-spoke delivery, and set $D^d \leftarrow D^d \backslash \{(N_i, C_j) | S_{ij}^{dh} \geq 0\}$, $D^h \leftarrow D^h \cup \{(N_i, C_j) | S_{ij}^{dh} \geq 0\}$.

Step 4.2. If case 2 appears, then for every replenishment arc $(N_i, C_j) \in D^h$, compute S_{ij}^{hd}, which is an estimate of the improvement in the solution value if the replenishment arc is transferred from D^h to D^d. Transfer all those pairs with positive S_{ij}^{hd} from direct shipment delivery to hub-and-spoke delivery, and set $D^h \leftarrow D^h \backslash \{(N_i, C_j) | S_{ij}^{hd} > 0\}$, $D^d \leftarrow D^d \cup \{(N_i, C_j) | S_{ij}^{hd} > 0\}$.

Step 5. Solve the mixed-collaborative delivery problem with demand partition $\{D^d, D^h\}$, and record the total emergency rescue cost as TC'.

Step 6. Compare the TC^s and TC', if $TC' < TC^s$, let $TC^s \leftarrow TC'$ and record the partition $\{D^d, D^h\}$. Thus, TC^s is the value of the best solution obtained so far, if $TC^s < TC^m$, let $TC^m \leftarrow TC^s$.

Step 7. Let $j = j + 1$, go back to the Step 4, if top limit of j is satisfied, go to the next step.

Step 8. Let $i = i + 1$, go back to the Step 4, if top limit of i is satisfied, go to the next step.

Step 9. End the programme and output the optimal result.

Since S_{ij}^{dh} or S_{ij}^{hd} are updated at every iteration and for more results on this topic, we refer readers to Liu et al. [12]. In what follows, we will test how well the model may be applied in the real world.

6.4 A Numerical Example and Implications

6.4.1 A Numerical Example

In this section, we rely on a numerical analysis to demonstrate the efficiency of the proposed method for the multi-level emergency logistics network when suffered a bioterror attack. Since the focus of this study is placed on the third emergency rescue stage, and goal of the optimization model is to better control the total emergency rescue cost and the inventory level in the local health departments, thus, the subsequent numerical example will be focused on the analysis of these two objectives. We assume that a region is suffered from a smallpox attack. There are 8 epidemic areas, 6 urban health departments and 3 national strategic storages in such region. The values of the parameters in the epidemic diffusion model are given in Table 6.1.

Taking the epidemic area 1 as the example, Fig. 6.5 is the numerical simulation of the epidemic model in this disaster area. The four curves respectively represent the

Table 6.1 Values of the parameters in SEIR epidemic diffusion model

Area	1	2	3	4	5	6	7	8
$S(0)$	5×10^3	4.5×10^3	5.5×10^3	5×10^3	6×10^3	4.8×10^3	5.2×10^3	4×10^3
$E(0)$	30	35	30	40	25	40	50	45
$I(0)$	5	6	7	8	4	7	9	10
$R(0)$	0							
β	4×10^{-5}							
$\langle k \rangle$	6							
δ	0.3							
d	1×10^{-3}							
τ	5							

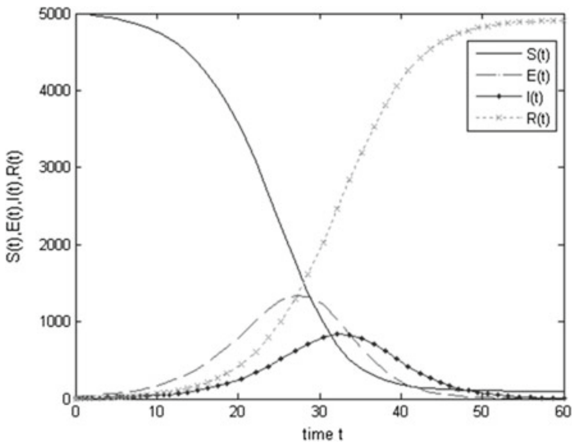

Fig. 6.5 Solution of the SEIR epidemic diffusion model (epidemic area 1)

number of four groups of people (S, E, I, R) as time goes by. As this study focuses the third emergency rescue, we assume that it runs from the 45th day (rescue cycle $t = 0$) to the 55th day (rescue cycle $t = 10$). Meanwhile, the rescue cycle is set to be one day. Thus, a total of 8640 arcs are generated and used in the experiment).

Let $a = 1$, $\theta = 90\%$ and $\Gamma = 15$ (days), the 'DDE23 tool' in MATLAB coupled with Eqs. (6.18)–(6.20) are adopted to forecast the time-varying demand for each epidemic area from time $t = 0$ to $t = 10$. As before, taking the epidemic area 1 as the example, demand of the emergency resources at each rescue cycle by both of the time-varying and traditional forecast models are shown in the Fig. 6.6.

As Fig. 6.6 shows, the forecasting model for time-varying demand can reflect the effectiveness that emergency resources allocated in the early rescue cycle will affect the demand in the following periods efficiently. The time-varying demand of emergency resources is reduced obviously when compared with the traditional demand in the following periods. It is worth to mentioning that both these two curves get a similar variation tendency, which represents the epidemic is going to be controlled. After getting demand of emergency resources in each rescue cycle, in what follows, we will focus on how to allocate emergency resources to the epidemic areas, and at the same time, how to replenish emergency resources to each urban health department, with the objective of minimizing the total emergency rescue cost. Table 6.2 shows the unit transportation cost from the supply point to the demand point in the emergency logistics network (Suppose that national strategic storage 1 is preset as the HUB location).

As mentioned before, we assume that each national strategic storage can supply a certain amount of emergency resources in each rescue cycle. Let they be 400, 420 and 450, and let the capacity of the urban health department be 210. Take the emergency allocation result at time $t = 0$ as the example, we can solve the programming model according to the solution procedure (As introduced in Sect. 6.4). The initial solution is reported in Table 6.3 (Total cost 6576.24). Then, the heuristic algorithm is adopted

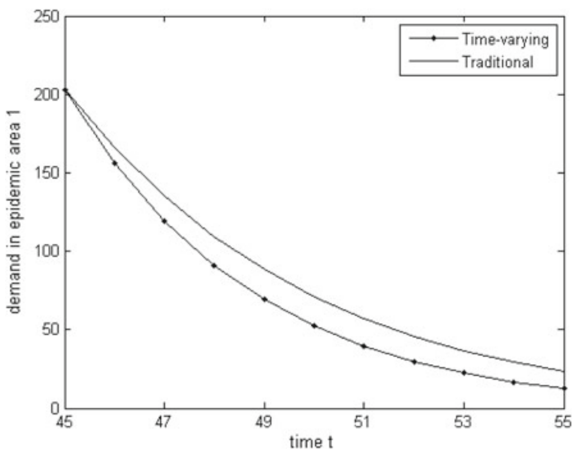

Fig. 6.6 Demand of the emergency resources in epidemic area 1

Table 6.2 Unit transportation cost between two different points

Cost	N1	C1	C2	C3	C4	C5	*C6*	
N1	–	2	9	1	3	10	2	
N2	4	7	2	10	8	9	8	
N3	5	10	8	2	9	2	8	
	E1	E2	E3	E4	E5	E6	E7	E8
C1	6	2	6	7	4	2	5	9
C2	4	9	5	3	8	5	8	2
C3	5	2	1	9	7	4	3	3
C4	7	6	7	3	9	2	7	1
C5	2	3	9	5	7	2	6	5
C6	5	5	2	2	8	1	4	3

Table 6.3 Solution of the optimization model at time $t = 0$

Amount		N1	C1	C2	C3	C4	C5	C6
Before the adjustment	N1	–	106	–	–	94	–	200
	N2	–	104	210	–	106	–	–
	N3	–	–	–	210	10	210	10
After the adjustment	N1	–	210	–	–	210	–	210
	N2	210	–	210	–	–	–	–
	N3	20	–	–	210	–	210	–
	E1	E2	E3	E4	E5	E6	E7	E8
C1	–	81.8	–	–	128.2	–	–	–
C2	29.3	–	–	117.5	–	–	–	12.8
C3	–	114.3	55.8	–	–	–	39.9	–
C4	–	–	–	–	–	35.4	–	174.6
C5	173.4	36.6	–	–	–	–	–	–
C6	–	–	38.2	–	–	124.7	47	–

to adjust and improve the solution, and thus, the final solution is obtained (Total cost 6346.24).

As Table 6.3 shows, while the replenishment arcs $(N_2, C_1) \in D^d$, $(N_2, C_4) \in D^d$, $(N_3, C_4) \in D^d$ and $(N_3, C_6) \in D^d$ are transferred from the direct shipment delivery system to the hub-and-spoke delivery system, the total rescue cost can be reduced. Our test on the selected problem instance shows that the mixed-collaborative system can save 5.9% of the rescue cost compared with the cost before the adjustment. And at last, a mixed-collaborative replenishment system is conducted for the upper level sub-problem. Actually, to better control the total emergency rescue cost, the decision maker can adjust and improve the initial solution of the lower level sub-problem as similar to the above way.

In a similar way, we can complete the whole operations according to the solution procedure (Fig. 6.4), then we can obtain the optimal initial solution for each rescue cycle. Then, the heuristic algorithm is adopted to adjust and improve the solution for each cycle. Replenishment arcs which need to be transferred in each cycle are shown in Table 6.4. At last, the final solution and the total emergency rescue cost for each cycle can be obtained.

Figure 6.7 shows the change in total rescue cost as time goes by. From this figure, we can get the following two conclusions: (1) Coupled with Fig. 6.6, we can see that demand of emergency resources becomes less and less, which implies that the epidemic diffusion situation is going to be stable and the spread of the epidemic is going to be under control. (2) Coupled with Table 6.4, we can see that the total rescue cost can be reduced by the proposed heuristic algorithm in a certain degree. It is worth mentioning that there is no adjustment after the rescue cycle $t = 4$, that's because the national strategic storages which are adjacent to the epidemic areas will have stored

Table 6.4 Transferred arcs in each cycle

Cycle	Arcs need to be transferred		Cycle	Arcs need to be transferred	
	Before	After		Before	After
$t = 0$	$N2 \rightarrow C1$ $N2 \rightarrow C4$ $N3 \rightarrow C4$ $N3 \rightarrow C6$	$N2 \rightarrow N1 \rightarrow C1$ $N2 \rightarrow N1 \rightarrow C4$ $N3 \rightarrow N1 \rightarrow C4$ $N3 \rightarrow N1 \rightarrow C6$	$t = 1$	$N2 \rightarrow C1$ $N2 \rightarrow C4$	$N2 \rightarrow N1 \rightarrow C1$ $N2 \rightarrow N1 \rightarrow C4$
$t = 2$	$N2 \rightarrow C1$ $N2 \rightarrow C4$	$N2 \rightarrow N1 \rightarrow C1$ $N2 \rightarrow N1 \rightarrow C4$	$t = 3$	$N2 \rightarrow C1$ $N2 \rightarrow C4$	$N2 \rightarrow N1 \rightarrow C1$ $N2 \rightarrow N1 \rightarrow C4$

Note There is no adjustment when $t = 4, 5, 6, 7, 8, 9, 10$

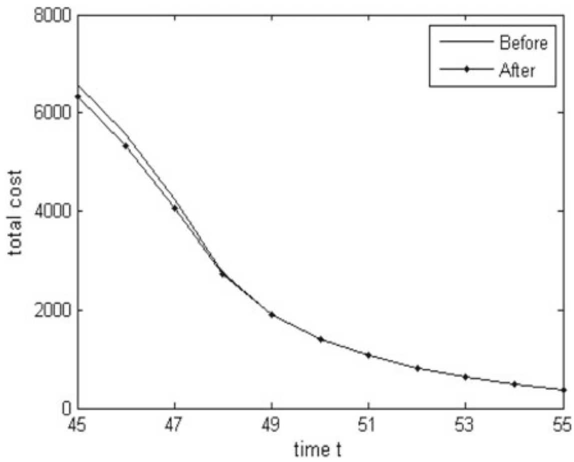

Fig. 6.7 Total rescue cost for each rescue cycle

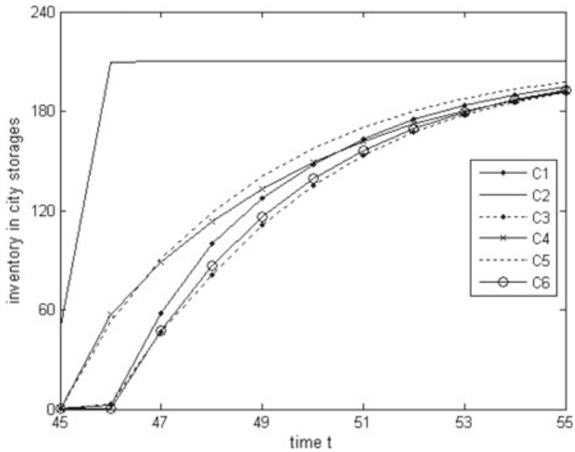

Fig. 6.8 Inventory level in different urban health departments as time goes by

enough emergency resources at that time, and thus, the emergency logistics network will be simplified greatly by then.

As mentioned before, the other control target of the optimization model is to better control the inventory level of the local urban health departments. Figure 6.8 implies that inventory level in each urban health department has been improved and raised as time goes by. Therefore, with the application of the integrated and dynamic optimization model, the total emergency rescue cost can be controlled effectively, and meanwhile, inventory level in each urban health department can be restored and raised gradually. Thus, such optimization model achieves a win-win emergency rescue effect in anti-bioterrorism system.

6.4.2 A Short Sensitivity Analysis

From the previous analysis we can see that the change in total rescue cost mainly depends on the change in demand. In this section, a short sensitivity analysis of the key parameters (θ and Γ) in the forecasting model for the time-varying demand is conducted.

Taking the total rescue cost at time $t = 10$ as the example, holding all the other parameters fixed as in the numerical example given in Sect. 6.4.1, except that θ and $\mathit{\Gamma}$ take on five different values, respectively. The changes in total rescue cost are shown in Figs. 6.9 and 6.10. As Fig. 6.9 shows, θ takes on five values ranging from 60% to 100% with an increment of 10%, we can obtain the following conclusion: the larger the θ is, the higher of the actual effective rescue rate in each cycle is, thus, the less of demand is, and finally, the lower of the total rescue cost is. Similarly, as Fig. 6.10 shows, Γ takes on five values ranging from 9 to 21 with an increment of 3. Conversely, the larger of Γ is, the longer of the treatment cycle is, thus, the larger of the demand of emergency resources is, and finally, the higher of the total rescue

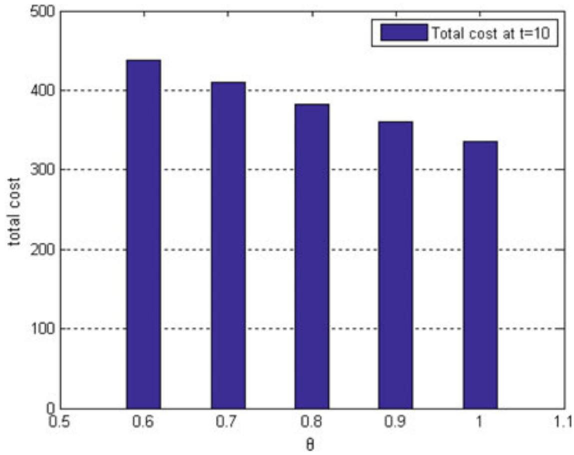

Fig. 6.9 Change in total rescue cost with different value of θ ($t = 10$)

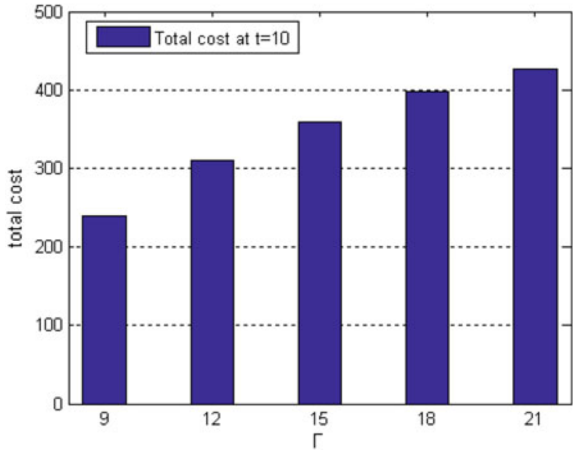

Fig. 6.10 Change in total rescue cost with different value of Γ ($t = 10$)

cost is. The above analysis confirms that both of the two key parameters play an important role in the emergency decisions. For a small change of θ and Γ, the total rescue cost at each cycle can change significantly. Unfortunately, precise value of these two parameters for an epidemic is difficult to get. As the accuracy of these two parameters is vital to the success of emergency rescue, a great deal of effort needs to be devoted to scientifically estimating these two parameters of different epidemics.

Overall, to enhance the emergency rescue effectiveness in the anti-bioterrorism system, we should improve our rescue work from the following aspects:

(1) Once suffered from a bioterror attack, the epidemic area should be isolated from other areas to avoid the spread of the disease as far as possible.

(2) Demand of the emergency resources in the epidemic area should be forecasted quickly and precisely, for medicine in such emergency period is precious and should not be wasted.
(3) An effective, integrated and dynamic optimization model should be conducted for the emergency logistics network so that a win-win emergency rescue effect will be achieved.
(4) There should be enough emergency resources to cure the patients so that the actual effective rescue rate and the treatment time for each infected person can be improved, and then, the epidemic diffusion can be controlled effectively.

6.5 Conclusions

In this chapter, the optimal decision of the multi-level emergency logistics network with uncertain demand is investigated. An integrated and dynamic optimization model is developed, and an effective solution procedure is designed. To verify the validity and the feasibility of the solution procedure, we have presented a numerical example and an accurate result is obtained in a short amount of time. The main differences distinguish this study to the past literature are presented as follows.

(1) With the consideration of that emergency resources allocated in the early rescue cycle will affect the demand in the following periods, a unique forecast mechanism to predict the demand in the epidemic area is proposed. Furthermore, we construct two forecasting models for the time-varying demand and inventory level in urban health department.
(2) A win-win emergency rescue effect is achieved by the integrated and dynamic optimization model. The total emergency rescue cost is controlled effectively, and meanwhile, inventory level in each urban health department is restored and raised gradually.
(3) Emergency planning has always been formulated as vehicle routing problem (VRP), or vehicle routing problem with time windows (VRPTW) in the precious literature, which includes many sub-tour constraints and is difficult to solve. Further more, time duration factor is not incorporated into the decision, resulting in incomplete decisions in real operations. In this study, the emergency problem has been decomposed into several mutually correlated sub-problems, and then be solved systematically in the same decision scheme. Thus, the result will be suitable to the real operations much better.

To summarize, in this study, emergency logistics network in the anti-bioterrorism system has been optimized from the perspective of integration. And we have achieved the win-win rescue goal. However, it's also necessary to point out some limitations of this research. First of all, we assume that once suffered from a bioterror attack, each epidemic area can be isolated from other areas to avoid the spread of the disease. Second, emergency resources in the anti-bioterrorism system may include vaccine, antibiotics, masks and so on, thus, the emergency logistics problem should be a multi-commodity problem. Third, to facilitate the calculation process, initial inventory and capacity of the urban health departments are assumed ideally. The situations in actual operations would be much more complex. All these areas represent our future research directions.

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