

Chapter 13

Epidemic-Logistics Network Considering Time Windows and Service Level



In this chapter, we present two optimization models for optimizing the epidemic-logistics network. In the first one, we formulate the problem of emergency materials distribution with time windows to be a multiple traveling salesman problem. Knowledge of graph theory is used to transform the MTSP to be a TSP, then such TSP route is analyzed and proved to be the optimal Hamilton route theoretically. Besides, a new hybrid genetic algorithm is designed for solving the problem. In the second one, we propose an improved location-allocation model with an emphasis on maximizing the emergency service level. We formulate the problem to be a mixed-integer nonlinear programming model and develop an effective algorithm to solve the model. In this chapter, we present two optimization models for optimizing the epidemic-logistics network. In the first one, we formulate the problem of emergency materials distribution with time windows to be a multiple traveling salesman problem. Knowledge of graph theory is used to transform the MTSP to be a TSP, then such TSP route is analyzed and proved to be the optimal Hamilton route theoretically. Besides, a new hybrid genetic algorithm is designed for solving the problem. In the second one, we propose an improved location-allocation model with an emphasis on maximizing the emergency service level. We formulate the problem to be a mixed-integer nonlinear programming model and develop an effective algorithm to solve the model.

13.1 Emergency Materials Distribution with Time Windows

13.1.1 Introduction

With rapid development of the global economy, a new biological virus can get anywhere around the world in 24 h. Virus which lurked in the forest or other biological environment before, have been forced to face human ecology when its nature ecology environment destroyed, and this would cause some new type diseases such as Mar-

burg hemorrhagic fevers in Angola, SARS in China, Anthrax mail in USA, Ebola in Congo, smallpox and so on. Bioterrorism threats are realistic and it has a huge influence on social stability, economic development and human health. Without question, nowadays the world has become a risk world, filling with all kinds of threaten from both nature and man made.

Economy would always be the most important factor in normal materials distribution network. However, timeliness is much more important in emergency materials distribution network. To form a timeliness emergency logistics network, a scientific and rational emergency materials distribution system should be constructed to cut down the length of emergency rescue route and reduce economic loss.

In 1990s, America had invested lots of money to build and perfect the emergency warning defense system of public health, aiming to defense the potential terrorism attacks of biology, chemistry and radioactivity material. Metropolitan Medical Response System (MMRS) is one of the important parts, which played a crucial role in the "9.11" event and delivered 50 tons medicine materials to New York in 7 h [1]. In October 2001, suffered from the bioterrorism attack of anthrax, the federal medicine reserve storage delivered a great deal of medicine materials to local health departments [2].

Khan et al. [3] considered that the key challenge of anti-bioterrorism is that people don't know when, where and in which way they would suffer bioterrorism attack, and what they can do is just using vaccine, antibiotics and medicine to treat themselves after disaster happened. Because of this, Venkatesh and Memish [4] mentioned that what a country most needed to do is to check its preparation for bioterrorism attacks, especially the perfect extent of the emergency logistics network which includes the reserve and distribution of emergency rescue materials, and the emergency response ability to bioterrorism attacks. Other anti-bioterrorism response relative researches can be found in Kaplan et al. [5].

Emergency materials distribution is one of the major activities in anti-bioterrorism response. Emergency materials distribution network is driven by the biological virus diffusion network, which has different structures from the general logistics network. Quick response to the emergency demand after bioterrorism attack through efficient emergency logistics distribution is vital to the alleviation of disaster impact on the affected areas, which remains challenges in the field of logistics and related study areas [6].

In the work of Cook and Stephenson [7], importance of logistics management in the transportation of rescue materials was firstly proposed. References Ray [8] and Rathi et al. [9] introduced emergency rescue materials transportation with the aim of minimizing transportation cost under the different constraint conditions. A relaxed VRP problem was formulated as an integer programming model and proved that's a NP-Hard problem in Dror et al. [10] Other scholars have also carried out much research on the emergency materials distribution models such as Fiedrich et al. [11], Ozdamar et al. [12] and Tzeng et al. [13].

During the actual process of emergency material distribution, the Emergency Command Center(ECC) would always supply the emergency materials demand points(EMDP) in groups based on the vehicles they have. Besides, each route

wouldn't repeat, which made any demand point get the emergency materials as fast as possible. To the best of our knowledge, this is a very common experience in China. Under the assumption that any demand point would be satisfied after once replenishment, the question researched would be turn into a multiple traveling salesman problem (MTSP) with an immovable origin. In the work of Bektas [14], the author gave a detailed literature review on MTSP from both sides of model and algorithm. Malik et al. [15], Carter and Ragsdale [16] illustrate some more results on how to solve the MTSP.

To summarize, our model differs from past research in at least three aspects. First, nature disaster such as earthquake, typhoons, flood and so on was always used as the background or numerical simulation in the past research, such kind of disaster can disrupt the traffic and lifeline systems, obstructing the operation of rescue machines, rescue vehicles and ambulances. But situation in anti-bioterrorism system is different, traffic would be normal and the epidemic situation could be controlled with vaccination or contact isolation. Second, to the best of our knowledge, this is the first time to combine research on the biological epidemic model and the emergency materials distribution model, and we assume that emergency logistics network is driven by the biological virus diffusion network. Therefore, it has a different structure from the general logistics network. Third, the new hybrid genetic algorithm we designed and applied in this study is different from all the traditional ways, we improved the two-part chromosome which proposed by Carter and Ragsdale [16], and custom special set order function, crossover function and mutation function, which can find the optimal result effectively.

13.1.2 SIR Epidemic Model

Although rule of the virus diffusion isn't the emphasis in our research, it is the necessary part when depicting the emergency demanded. Figure 13.1 illustrates SIR epidemic model with natural birth and death of the population.

Then we can get the mathematic formulas as follows.

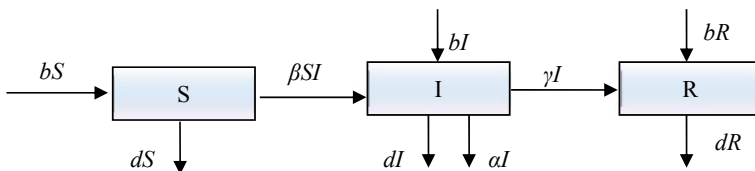


Fig. 13.1 SIR model with natural birth and death

$$\begin{cases} \frac{dS}{dt} = (b - d)S - \beta SI \\ \frac{dI}{dt} = \beta SI + (b - \gamma - d - \alpha)I \\ \frac{dR}{dt} = bR + \gamma I - dR \end{cases} \quad (13.1)$$

where S , I and R , represent number of the susceptible, infective and recovered population, respectively. b and d , stand for the natural birth and death coefficient, α is the death coefficient for disease, β is the proportion coefficient from S to I in unit time, and last, γ is the proportion coefficient from I to R .

Note that number of the susceptible and the infective persons would be gotten via computer simulation with value of the other parameters preset. Then, the emergency materials each point demanded can be also calculated based on the number of sick person.

13.1.3 Emergency Materials Distribution Network with Time Windows

Figure 13.2 is the roadway network of a city in south China, numbers beside the road are the length of the section (unit: km). Point O is the ECC and the other nodes 1–32 are the EMDPs. Now, there are some emergency materials arrived at the ECC by air transport and we need to send it to each demand point as fast as possible. We assumed that all the EMDPs are divided into 4 groups, and any demand point in the network would be satisfied after once replenishment, then the question researched was turn into a MTSP with an immovable origin. However, time windows constraint wasn't considered.

In this study, we use the new hybrid GA to solve the MTSP with time windows. Using SIR epidemic model in Sect. 13.2, number of the susceptible and infective people can be forecasted before emergency distribution. Then symbol t_i is set to show how much time is consumed in demand point i , $i = 1, 2, \dots, 32$. We assume it has a simple linear functional relationship with number of the infective person as follows.

$$t_i = \frac{I_i}{v_{vac}} \quad (13.2)$$

where I_i is number of the infective people in demand point i , v_{vac} is the average speed of vaccination. Another assumption for this research is that vehicle speed is the same as in any roadway section in the network, which noted as a symbol V . So, question researched in this study is: Based on the epidemic model analysis, how can we distribute the emergency materials to the whole EMDPs with a time windows constraint? How many groups should be divided? And, how can we get the optimization route? With the analysis above, objective function model can be formulated as follows.

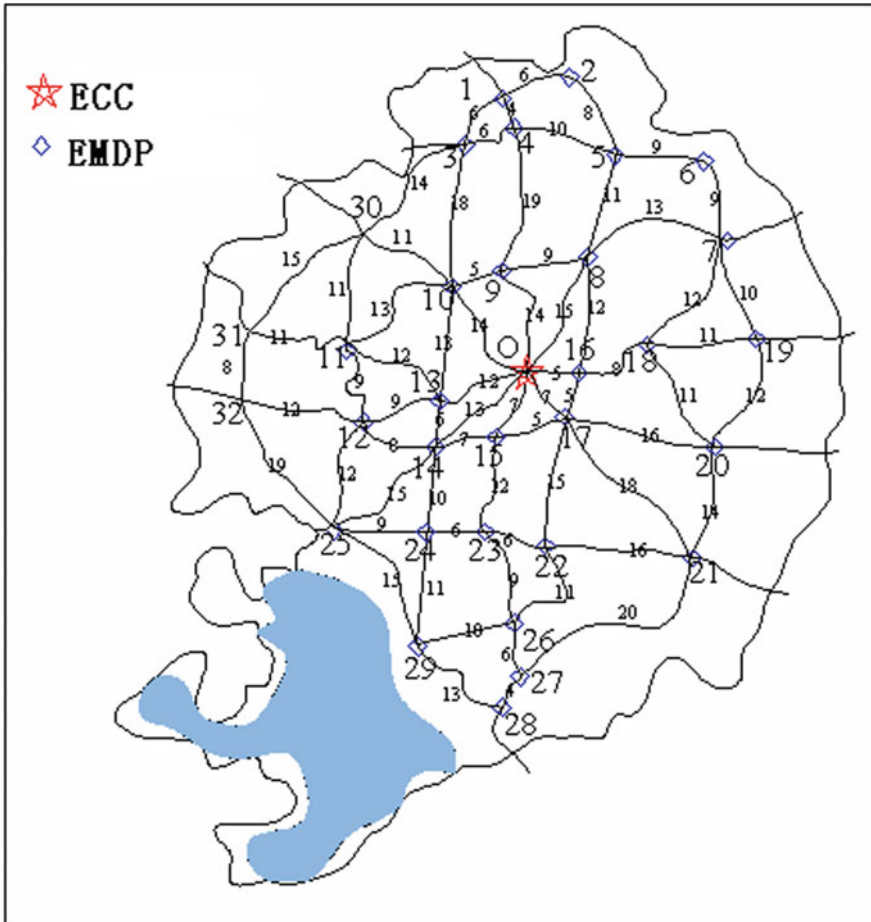


Fig. 13.2 Roadway network of the city

$$\min \sum_{i=1}^{32} \sum_{j=1}^{32} \frac{s_{ij}x_{ij}}{V} + \sum_{i=1}^{32} t_i \tag{13.3}$$

$$s.t. \sum_{j=1}^{32} x_{oj} = n \tag{13.4}$$

$$\sum_{j=1}^{32} x_{jo} = n \tag{13.5}$$

$$\sum_{i=1}^{32} x_{ij} = 1, \forall j = 1, 2, \dots, 32 \tag{13.6}$$

$$\sum_{j=1}^{32} x_{ij} = 1, \forall i = 1, 2, \dots, 32 \quad (13.7)$$

$$\sum_{i \notin S} \sum_{j \in S} x_{ij} \geq 1, \forall S \subseteq V \setminus \{O\}, S \neq \emptyset \quad (13.8)$$

$$T_k \leq T_{TW}, k = 1, 2, \dots, n \quad (13.9)$$

$$x_{ij} \in \{0, 1\}, \forall (i, j) \in G \quad (13.10)$$

where $x_{ij} = 1$ means that the emergency materials is distributed to point j immediately after point i , otherwise, $x_{ij} = 0$. s_{ij} represent the shortest route between point i and j . n is number of the distribution groups. T_k is time consumed in group k . T_{TW} is the time windows. Equations (13.4) and (13.5) are the grouping constraints, (13.6) and (13.7) insure that each demand point would be supplied once. Equation (13.8) assures that there is no sub loop in the optimal route. Equation (13.9) is the time windows constraint. And last, Eq. (13.10) is the parameter specification. The hybrid genetic algorithm are presented as follows.

Step 1: Using SIR epidemic model in Sect. 13.2 to forecast number of the susceptible and infective people, and then, confirm the emergency distribution time in each EMDP;

Step 2: Generate the original population based on the code rule;

Step 3: Using the custom set order function to optimize the original population and make the new population have finer sequence information;

Step 4: Estimate that whether the results satisfy the constraints (4) to (10) in the model, if yes, turn to the next step, if not, delete the chromosome;

Step 5: Using the fitness function to evaluate fitness value of the new population;

Step 6: End one fall and the best one doubled policy are used to copy the population;

Step 7: Crossover the population using the custom crossover function;

Step 8: Mutate the population using the custom mutation function;

Step 9: Repeat the operating procedures (3)–(8) until the terminal condition is satisfied;

Step 10: 10 approximate optimal routes would be found by the new hybrid genetic algorithm and then the best equilibrium solution would be selected by the local search algorithm.

13.1.4 Numerical Tests

In order to evaluate the practical efficiency of the proposed methodology, parameters of the SIR epidemic model are given as follows, $b = d = 10^{-5}$, $\beta = 10^{-5}$, $\alpha = 0.01$, $\gamma = 0.03$, and initializing $S = 10,000$, $I = 100$, $R = 0$. $v_{vac} = 2000$,

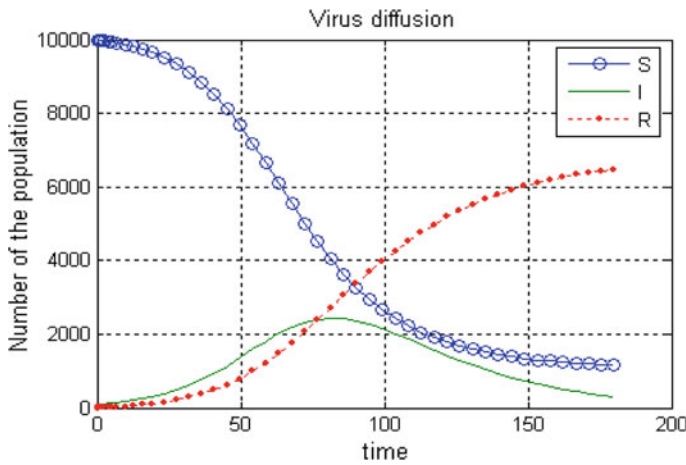


Fig. 13.3 Virus diffusion with time

$T_{TW} = 12$, $V = 40$, $Day = 5$. And we assume that each EMDP has the same situation. Figure 13.3 illustrates that number of the susceptible and infective people changed. Similarly, with different initial value of the S_i and I_i in different EMDP, number of the susceptible and infective people in any EMDP and any time can be forecasted, and then, time consumed in each demand point can be calculated. Figure 13.4 illustrates the magnitude of the differences in the solution spaces for the

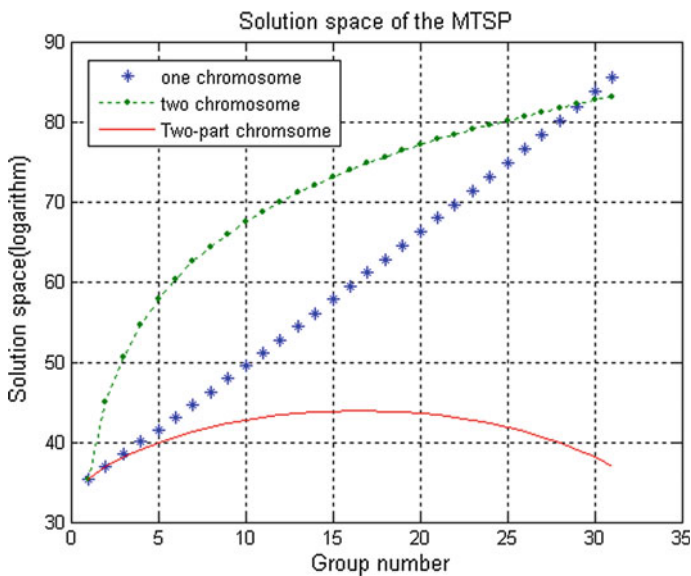


Fig. 13.4 Solution space of the MTSP

three chromosomes for a MTSP with $n = 32$ demand points as the group number is varied from 1 to 32. From this figure we can see that when $n \geq 4$, size of the solution space in Two-part chromosome is distinguish to the other two styles.

Figures 13.5 and 13.6 show the fitness and route length vary with iterate times using the new hybrid GA, respectively. From the figures we can see that each group would be converged effectively, 10 approximate optimal routes would be obtained.

Comparison of the 10 approximate optimal routes is illustrated in Fig. 13.7, and the best equilibrium solution of emergency materials distribution is shown in Fig. 13.8.

From Figs. 13.6 and 13.7, though length of the route in group 9 is the shortest one, it isn't the best equilibrium solution. In other words, some demand points can be supplied immediately but others should wait for a long time. This is not the objective we pursue. From Fig. 13.7, inside deviation of group 7 is the minimum one, which means route in group 7 is the best equilibrium solution, though it isn't the shortest route. In other words, all the demand points can be supplied in the minimum time difference at widest possibility. Another problem worthy to be pointed out is that group 10 is the suboptimal to group 7, and this can be used as a candidate choice for commander under the emergency environment.

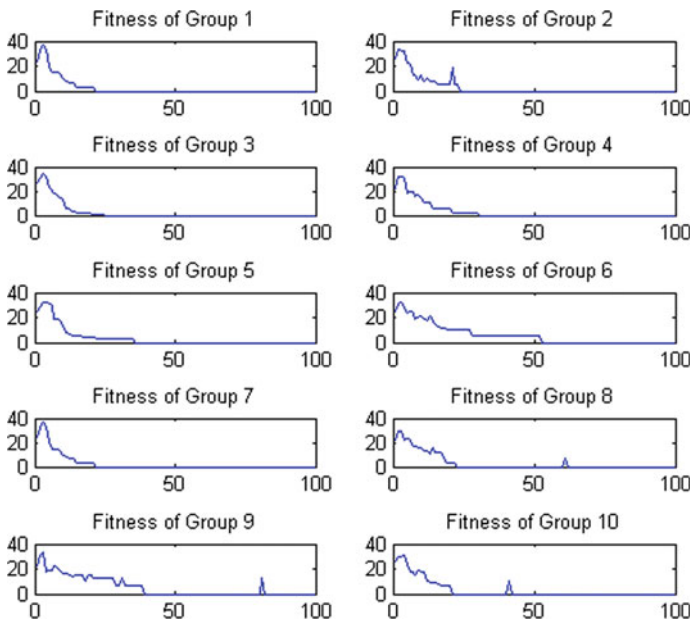


Fig. 13.5 Fitness with iteration

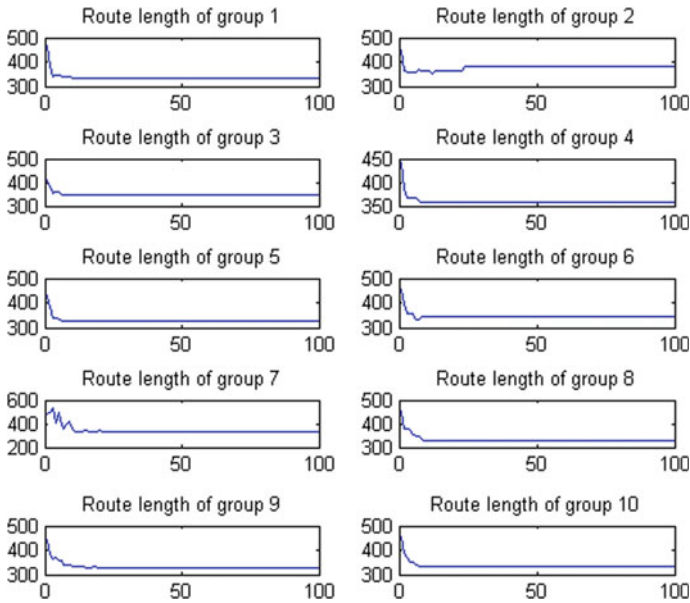


Fig. 13.6 Route length with iteration

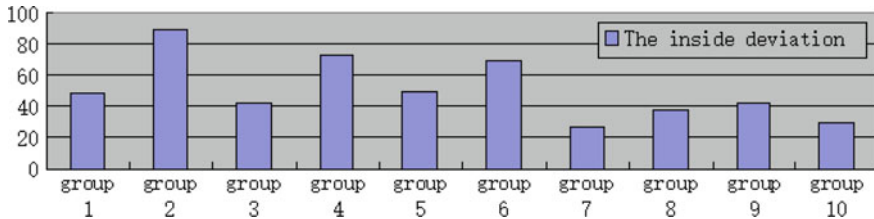


Fig. 13.7 The inside deviation of each group

13.1.5 Discussion

In fact, results in the prior section are too idealized, for we just considered emergency materials distribution at the beginning of the virus diffusion ($Day = 5$) and we assume that each EMDP has the same situation. In fact, it is impossible. Each parameter preset would affect the result at last immensely. Some of them are discussed as follows.

(1) Time consumed with different initial size of S

There are 32 EMDPs in this distribution network, actually, each point has a different number of the susceptible people to others, and we can assume they are distributed from 10,000 to 50,000. With the SIR epidemic model in Sect. 13.1.2, different size

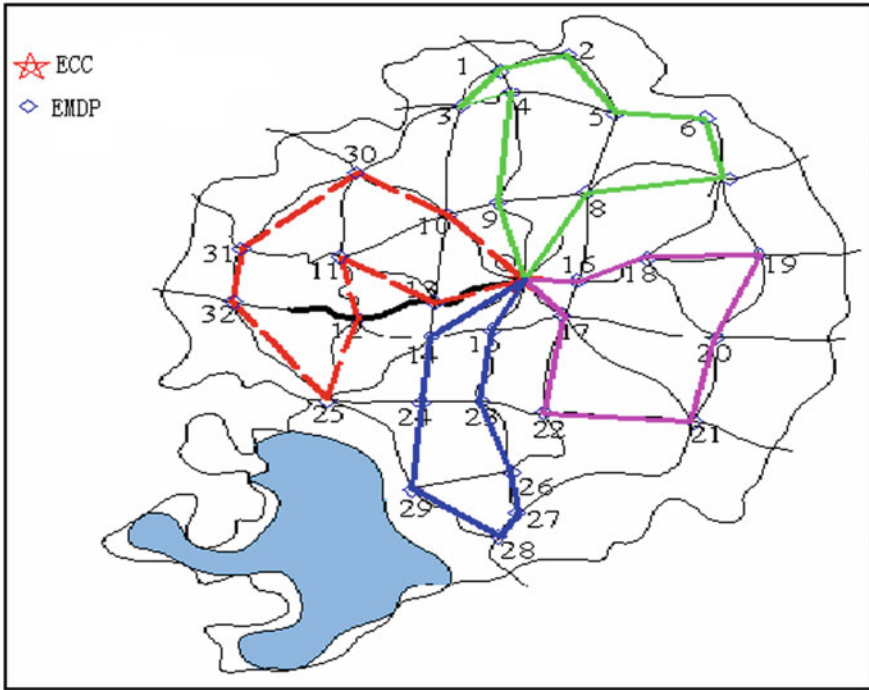


Fig. 13.8 Best equilibrium solution of the MTSP

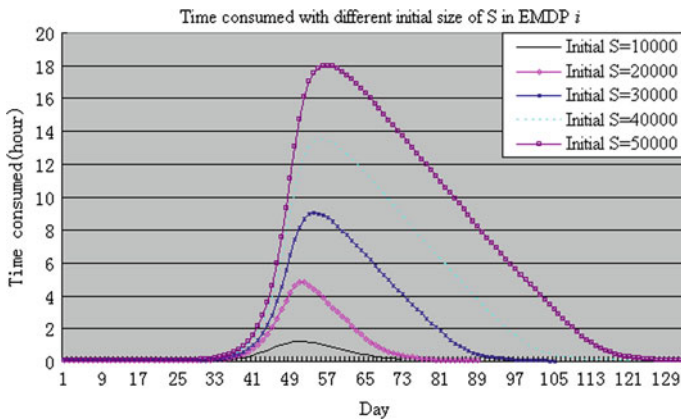


Fig. 13.9 Time consumed with different initial size of S

of the initial susceptible people will bring different size of infective people at last, and then, time consumed in these EMDPs would be varied. Figure 13.9 illustrates that time consumed in one EMDP with different initial size of S as date increased.

There is almost no distinguish among them in the first 30 days (a month), however, distinguish is outstanding in the following days. The larger the initial size of S is, the faster increment speed of the time consumed. In Sect. 13.1.4, $S = 10,000$ is taken for each EMDP and the time consumed almost no more than 1 h, this is a very simple situation, and the optimal route with time windows can be depicted easily. But when initial size of S increased, the problem would become much more trouble for satisfying the time window constraint, and then, we should divided the distribution route in much more groups.

(2) **Time consumed with different initial size of I**

As mentioned before, each EMDP also has a different number of the infective people to others, and we can assume they are distributed from 50 to 200. Figure 13.10 illustrates that time consumed in one EMDP with different initial size of I as date increased. It also can get that time consumed in the first 30 days is smoothly, but distinguish is outstanding in the following days. Similar as before, the larger the initial size of I is, the faster increment speed of the time consumed. Another interesting result is that vary I from 50 to 200, distinguish of the time consumed in each situation isn't very outstanding, and size of the time consumed is around 1 h. In other words, model in Sect. 13.1.3 is still serviceable and we needn't change the grouping design.

(3) **Time consumed with different initial size of β**

β is one of the most important parameters in SIR epidemic model, it affects number of the infective people in the population directly, and then, it affects the time consumed in EMDP accordingly. Vary value of β from 10^{-5} to 5×10^{-5} , and we get time consumed with it changed as show in Fig. 13.11. Still we have conclusion that time consumed in the first 30 days is more or less in different situations, but distinguish is outstanding in the following days. Similar as before, the larger the initial size of β is, the faster increment speed of the time consumed. With initial size of β increased, distribution groups should be adjusted for satisfying the time windows.

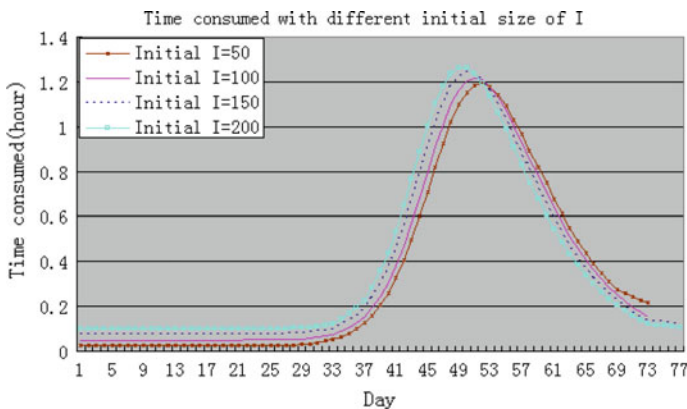


Fig. 13.10 Time consumed with different initial size of I

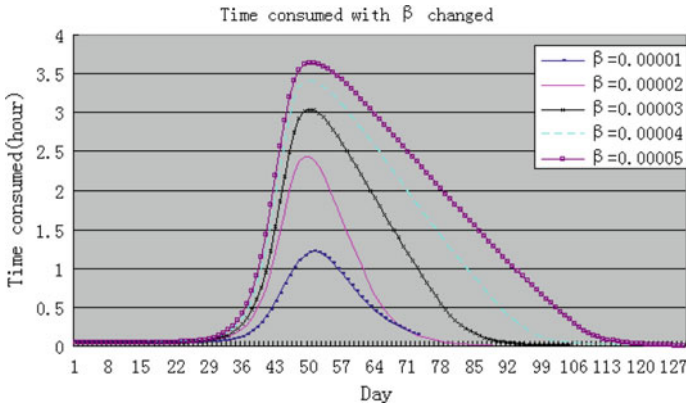


Fig. 13.11 Time consumed with different initial size of β

Based on the analysis above, we can see that time consumed in the first 30 days always stay in a lower level. It is important information for emergency relief in the anti-bioterrorism system, which means the earlier the emergency materials distributed, the less affect would be brought by parameters varied. This also answers the actual question that why emergency relief activities always get the best effectiveness at the beginning.

13.1.6 Conclusions

Emergency materials distribution problem with a MTSP characteristic in the anti-bioterrorism system is researched in this study, and the best equilibrium solution is obtained by the new hybrid GA. Modeling the MTSP using the new two-part chromosome proposed has clear advantages over using either of the existing one chromosome or the two chromosome methods. Besides, combined with the SIR epidemic model, relationship between the parameters and the result are discussed at last, which makes methods proposed in this study more practical.

A problem worthy to be pointed out is that the shortest route between any two EMDPs in the new hybrid GA is calculated by Dijkstra algorithm, so, the optimal result would be gotten even if some sections of the roadway are disrupted, which makes applicability range of the method projected in this study expanded. Research on the emergency materials distribution is a very complex work, only some idealized situations are analyzed and discussed in this study, and some other constraints such as loading capacity of the vehicles, death coefficient for disease, distribution mode and so on, which could be directions of further research.

13.2 An Improved Location-Allocation Model for Emergency Logistics Network Design

Emergency logistics network design is extremely important when responding to an unexpected epidemic pandemic. In this study, we propose an improved location-allocation model with an emphasis on maximizing the emergency service level (ESL). We formulate the problem to be a mixed-integer nonlinear programming model (MINLP) and develop an effective algorithm to solve the model. The numerical test shows that our model can provide tangible recommendations for controlling an unexpected epidemic.

13.2.1 Introduction

Over the past decade, various types of diseases have erupted throughout the world, i.e., SARS (2003), human avian influenza (2004), H1N1 (2009), and Ebola (2014–2015). These unconventional diseases not only seriously endanger humanity's life, but also have significant impacts on economic development. A recent example is the 2014–2015 Ebola pandemic occurring in West Africa, which infected 28,610 individuals, causing 11,300 fatalities and \$32.6 billion in economic losses.

To satisfy the emergency demand of epidemic diffusion, an efficient emergency service network, which considers how to locate the regional distribution center (RDC) and how to allocate all affected areas to these RDCs, should be urgently designed. This problem opens a wide range for applying the OR/MS techniques and it has attracted many attentions in recent years.

For example, Ekici et al. [17] proposed a hybrid model, which estimated the spread of influenza and integrated it with a location-allocation model for food distribution in Georgia. Chen et al. [18] proposed a model which linked the disease progression, the related medical intervention actions and the logistics deployment together to help crisis managers extract crucial insights on emergency logistics management from a strategic standpoint. Ren et al. [19] presented a multi-city resource allocation model to distribute a limited amount of vaccine to minimize the total number of fatalities due to a smallpox outbreak. He and Liu [20] proposed a time-varying forecasting model based on a modified SEIR model and used a linear programming model to facilitate distribution decision-making for quick responses to public health emergencies. Liu and Zhang [21] proposed a time-space network model for studying the dynamic impact of medical resource allocation in controlling the spread of an epidemic. Further, they presented a dynamic decision-making framework, which coupled with a forecasting mechanism based on the SEIR model and a logistics planning system to satisfy the forecasted demand and minimize the total operation costs [22]. Anparasan and Lejeune [23] proposed an integer linear programming model, which determined the number, size, and location of treatment facilities, deployed medical staff, located ambulances to triage points, and organized the transportation of severely ill patients

to treatment facilities. Büyüktaşkın et al. [24] proposed a mixed-integer programming (MIP) model to determine the optimal amount, timing and location of resources that are allocated for controlling Ebola in West-Africa. Moreover, literature reviews on OR/MS contributions to epidemic control were conducted in Dasaklis et al. [25], Rachaniotis et al. [26] and Dasaklis et al. [27].

In this study, we propose an improved location-allocation model for emergency resources distribution. We define a new concept of emergency service level (ESL) and then formulate the problem to be a mixed-integer nonlinear programming (MINLP) model. More precisely, our model (1) identifies the optimal number of RDCs, (2) determines RDCs' locations, (3) decides on the relative scale of each RDC, (4) allocates each affected area to an appropriate RDC, and (5) obtains ESL for the best scenario, as well as other scenarios.

13.2.2 Model Formulation

(1) Definition of ESL

In this study, ESL includes two components. ESL_1 is constructed to reflect the level of demand satisfaction and ESL_2 is proposed for the relative level of emergency operation cost. These two aspects are given by the weight coefficient α and $1 - \alpha$ respectively. The influence of these two factors on the ESL is illustrated in Fig. 13.12. Figure 13.12a represents that ESL_1 increases as the level of demand satisfaction raised. As we can see that it is a piecewise curve. Before demand is completely met, it is an S-shape curve from zero to α . After that, it becomes a constant, which means the additional emergency supplies cannot improve the ESL. Figure 13.12b identifies that ESL_2 decreases as the relative total cost increases. When emergency operation cost is minimized, the ESL_2 arrives at its best level of $1 - \alpha$. Similarly, when emergency operation cost is maximized, the ESL_2 is zero.

(2) Mathematic Model

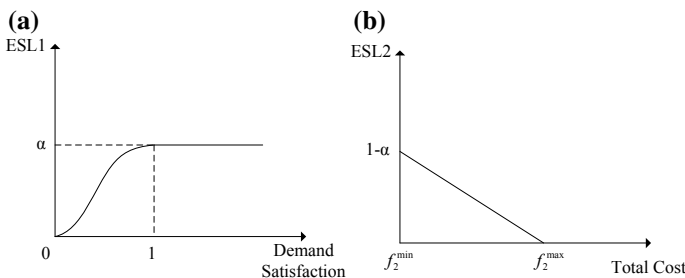


Fig. 13.12 Schematic diagram of ESL

Our model depicts the problem of location and allocation for emergency logistics network design. The network is a three-echelon supply chain of strategic national stockpile (SNS), RDCs, and affected areas. The core problem is to determine the number and locations for the RDCs. In each affected area, there is a point of dispensing (POD). To model the problem, we first present the relative parameters and variables as follows.

Parameters:

I : Set of SNSs, $i \in I$.

J : Set of RDCs, $j \in J$.

K : Set of affected areas, $k \in K$.

α : Weight coefficient for the two parts of ESL.

d_k : Demand for emergency supplies in affected area k .

(x_k, y_k) : Coordinates of affected area k .

(x_i, y_i) : Coordinates of SNS i .

C_{TL} : Unit transportation cost from SNS to RDC.

C_{LTL} : Unit transportation cost from RDC to affected area.

C_j^{RDC} : Cost for operating a RDC. It is decided by the relative size of the RDC j .

U_i : Supply capacity of SNS i .

Variables:

D_{ij} : Distance from SNS i to RDC j . For simplify, the Euclidean distance is adopted.

D_{jk} : Distance from RDC j to affected area k .

ε_{jk} : Binary variable. If RDC j provides emergency supplies to affected area k , $\varepsilon_{jk} = 1$; otherwise, $\varepsilon_{jk} = 0$.

z_j : Binary variable. If RDC j is opened, $z_j = 1$; otherwise, $z_j = 0$.

x_{jk} : Amount of emergency supplies from RDC j to affected area k .

y_{ij} : Amount of emergency supplies from SNS i to RDC j .

(x_j, y_j) : Coordinates of RDC j .

According to the above notations, we can define the optimization model as follows.

$$\text{Max } ESL = ESL_1 + ESL_2 \quad (13.11)$$

Herein, ESL_1 is defined as (13.12)–(13.14). These equations reflect that the less the unsatisfied demand is, the higher ESL_1 is.

$$ESL_1 = \alpha \frac{1}{K} \sum_{k=1}^K p_k(h) \quad (13.12)$$

$$p_k(h) = e^{\frac{-h_k}{1-h_k}} \quad (13.13)$$

$$h_k = 1 - \frac{\sum_{j=1}^J \varepsilon_{jk} x_{jk}}{d_k} \quad (13.14)$$

ESL_2 is defined as follows. First, we formulate the total operation cost as (13.15):

$$f_2 = C_{TL} \sum_{j=1}^J \sum_{i=1}^I z_j y_{ij} D_{ij} + C_{LTL} \sum_{j=1}^J \sum_{k=1}^K \varepsilon_{jk} x_{jk} D_{jk} + \sum_{j=1}^J z_j C_j^{RDC} \quad (13.15)$$

where C_j^{RDC} is the operating cost for RDC j when it is opened. It is decided by the relative size of the RDC, which can be expressed as:

$$C_j^{RDC} = f(s_j) \quad (13.16)$$

$$s_j = \frac{\sum_{k=1}^K x_{jk}}{\sum_{j=1}^J \sum_{k=1}^K x_{jk}}, \forall j \quad (13.17)$$

Second, to non-dimensionalize the cost function f_2 , we calculate the following two extreme values for Eq. (13.15).

$$\text{Min}_{\text{var} \in S} f_2(\text{var}) = f_2^{\min}, \text{Max}_{\text{var} \in S} f_2(\text{var}) = f_2^{\max} \quad (13.18)$$

$$F_2 = 1 - \frac{f_2(\text{var}) - f_2^{\min}}{f_2^{\max} - f_2^{\min}} = \frac{f_2^{\max} - f_2(\text{var})}{f_2^{\max} - f_2^{\min}} \quad (13.19)$$

$$ESL_2 = (1 - \alpha) F_2 \quad (13.20)$$

where var represents all variables and S represents the following constraints. f_2^{\min} and f_2^{\max} are the minimum and maximum values obtained by solving (13.15) without considering the ESL_1 . The definition of ESL_2 means that the lower the total operation cost is, the higher the ESL is. The constraints for the optimization model are given as follows:

$$\text{s.t. } \sum_{j=1}^J \varepsilon_{jk} = 1, \forall k \in K \quad (13.21)$$

$$\sum_{j=1}^J \varepsilon_{jk} x_{jk} \leq d_k, \forall k \in K; \quad (13.22)$$

$$\sum_{i=1}^I z_j y_{ij} = \sum_{k=1}^K \varepsilon_{jk} x_{jk}, \forall j \in J \quad (13.23)$$

$$\varepsilon_{jk} \leq z_j, \forall j \in J, k \in K \quad (13.24)$$

$$\sum_{j=1}^J z_j \leq J \quad (13.25)$$

$$\sum_{j=1}^J y_{ij} \leq U_i, \forall i \in I \quad (13.26)$$

$$z_j, \varepsilon_{jk} = \{0, 1\}, \forall j \in J, k \in K \quad (13.27)$$

$$x_{jk}, y_{ij} \in \mathbb{Z}_0^+, \forall i \in I, j \in J, k \in K \quad (13.28)$$

$$(x_j, y_j), \forall j \in J \text{ are continuous variables.} \quad (13.29)$$

Constraint (13.21) indicates that each affected area is serviced by a single RDC. Constraint (13.22) specifies that the supplies to each affected area should not be more than its demand. Constraint (13.23) is a flow conservation constraint. Constraint (13.24) shows that only the opened RDC can provide distribution service. Constraint (13.25) specifies the upper bound of RDC number. Constraint (13.26) is the supply capacity constraint of each SNS. Finally, constraints (13.27)–(13.29) are variables constraints.

13.2.3 Solution Procedure

The proposed model for emergency services network design is a MINLP model as it involves multiplication of two variables (i.e., $\varepsilon_{jk}x_{jk}$). More importantly, the optimization model includes a continuous facility location-allocation model with unknown number of RDCs. To avoid the complexity of such MINLP model, we modify it by adding two auxiliary variables. The detail of the modification was introduced in McCormick [28]. Our solution procedure integrates an enumeration search rule and a genetic algorithm (GA), which are applied iteratively. As GA is a mature algorithm [29], details of the GA process are omitted here. We summarize the proposed solution methodology as below.

Step 1: Data input and parameters setting, which includes $I, J, K, \alpha, d_k, (x_k, y_k), (x_i, y_i), C_{TL}, C_{LTL}$, and C_j^{RDC} and the related parameters for GA.

Step 2: Initialization. Generate the original population according to the constraints.

Step 3: Evaluation. Fitness function is defined as the reciprocal of ESL.

Step 4: Selection. Use roulette as the select rule.

Step 5: Crossover. Single-point rule is used.

Step 6: Mutation. A random mutation is applied.

Step 7: If termination condition is met, go to the next Step; else, return to Step 4.

Step 8: Output the results.

13.2.4 Numerical Test

(1) Data Setting

To clarify the effect of the model, we conduct a numerical test. Assuming there is an unexpected epidemic outbreak in a 100×100 square region with 10 affected areas in it. In the square region, only three SNSs can provide emergency supplies. Because at the early stage of the outbreak, there is a large demand for emergency supplies. The supply capacity of these SNSs is less than the total demand in affected areas, which are set at 700, 600 and 400 respectively. The coordinates of the SNSs and the affected areas are obtained in advance. The upper bound of RDC number is set to be 8. The cost of operating a RDC is defined as $6760 \times \sqrt{s_j}$. The demand in each affected area is randomly generated. Finally, unit transportation cost from SNS to RDC is set to be 80 and unit transportation cost from RDC to affected area is 160.

(2) Test Results

Based on the above data setting, we solve our model by using MATLAB software and obtain the results in Fig. 13.13. As it shows in this figure, one can observe that there is a trade-off between the two components of the ESL. In our example, we test the parameter α from 0.4 to 0.9, which means the demand satisfaction is more and more important in our decision making. The result shows that when α is equal to 0.6, the total ESL can arrive at its best value (0.9258). Beyond which it decreases again. In practice, the decision makers may have different value of α according to the actual needs. Correspondingly, it will lead to different ESL.

Our model also determines the optimal number, locations and relative sizes for the RDCs. The test results are shown in Table 13.1. For example, RDC1 deliver emergency supplies to affected areas 2, 7 and 9. Its relative size is 33.23%, which means emergency supplies transshipped in this RDC occupies the corresponding proportion in total emergency distribution.

Table 13.2 illustrates the proportion of demand satisfaction for each affected area. For an example, demand for emergency supplies in affected area 2 is 149, and all this area's demand is totally satisfied. However, one can also observe that demands in some areas are partly supplied due to the supply capacity limitation. For example, only 69.5% of the demand in affected area 1 is delivered.

Fig. 13.13 ESL with different scenario of α

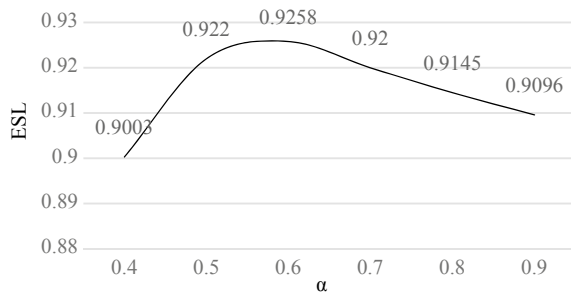


Table 13.1 Location and relative scale of each RDC

RDC	Location	Relative scale (%)	Affected area
1	(18.1651, 33.8696)	33.23	2, 7, 9
2	(38.2318, 39.6607)	10.24	10
3	(75.9550, 37.1063)	21.24	4, 6
4	(61.6731, 93.3449)	13.41	1, 5
5	(48.1101, 84.0045)	21.88	3, 8

Table 13.2 The proportion of demand satisfaction in each affected area

Number	Affected areas	Demand	Supply	Proportion (%)
1	(81.5, 15.7)	141	98	69.5
2	(90.6, 89)	149	149	100
3	(31.7, 85.7)	158	158	100
4	(48.5, 31.3)	170	170	100
5	(3.2, 70)	188	130	69.15
6	(8.7, 4.2)	191	191	100
7	(27.8, 42.1)	208	208	100
8	(54.7, 91.6)	214	214	100
9	(55.8, 79.2)	208	208	100
10	(36.4, 26)	233	174	74.68

(3) Sensitivity Analysis

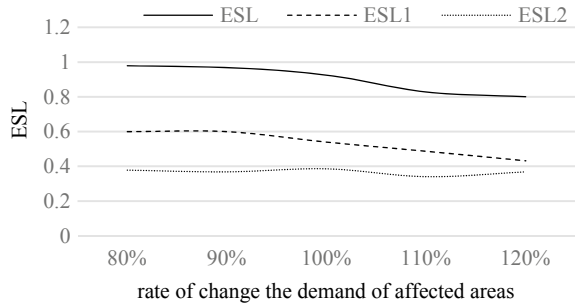
(1) Impact of α on the ESL

To understand the impact of α on the ESL, we solve our model with 6 different values of this parameter, meaning that decision makers have different considerations of the two components of the ESL. We compare the test result in Table 13.3. It can be observed that ESL_1 increases along with the emphasis on demand satisfaction. However, the actual proportion of ESL_1 is always staying at 90% of the setting of α .

Table 13.3 Sensitivity analysis on weight of ESL

α	ESL_1	Proportion (%)	ESL_2	Proportion (%)	ESL
0.4	0.3537	88.425	0.5466	91.1	0.9003
0.5	0.4381	87.62	0.4839	96.78	0.9220
0.6	0.5398	89.96	0.386	96.5	0.9258
0.7	0.6378	89.99	0.2822	94.07	0.9200
0.8	0.7269	90.86	0.1876	93.8	0.9145
0.9	0.8182	90.91	0.0914	91.4	0.9096

Fig. 13.14 ESL with different demand in affected areas



As to the ESL_2 , one can note that it increases at first and then decreases as α varied from 0.4 to 0.9.

(2) Sensitivity analysis on different demand in each affected area

We also examined the impact of different demand in each affected area. The test results are shown in Fig. 13.14. We change the original demand in each affected area for five scenarios. That means different demand situations when an unexpected infectious epidemic happened. One can easily observe the more the demand is, the lower the optimal ESL is. That is because when the demand increases, the supplies of SNSs remain original, which leads a reduction in ESL_1 . When the demand in each affected area changes, ESL_2 varies slightly. Which shows that the change of the total operation cost for the emergency logistics is not obvious when the scale of disease becomes smaller.

13.2.5 Conclusions

In this study, we propose an improved location-allocation model with an emphasis on maximizing the emergency service level (ESL). We formulate the problem to be a mixed-integer nonlinear programming model and develop an effective algorithm to solve the model. Moreover, we test our model through a case study and sensitivity analysis. The main contribution of this research is the function of ESL, which considers demand satisfaction and emergency operation cost simultaneously. Our definition of ESL is different from the existing literature and has a significant meaning for guiding the actual operations in emergency response. Future studies could address the limitations of our work in both the disease forecasting and logistics management. For example, the dynamics of epidemic diffusion could be considered and thus our optimization problem can be extended to a dynamic programming model.

References

1. Zhang H, Huang J, Hu Z. American metropolitan medical response system and its inspire for the foundation of the public healthy system in our country. *Chinese J Prevent Med.* 2004;38(4):276–8.
2. Li L. The discussion of orientation of Chinese public health in 21th century. *Chinese J Prevent Med.* 2001;35(4):219–20.
3. Khan AS. Public-health preparedness for biological terrorism in the USA. *Lancet.* 2000;356(9236):1179–82.
4. Venkatesh S, Memish ZA. Bioterrorism—a new challenge for public health. *Int J Antimicrob Agents.* 2003;21(2):200–6.
5. Kaplan EH, Craft DL, Wein LM. Analyzing bioterror response logistics: the case of smallpox. *Math Biosci.* 2003;185(1):33–72.
6. Sheu JB. An emergency logistics distribution approach for quick response to urgent relief demand in disasters. *Transport Res Part E: Logis Transport Rev.* 2007;43(6):687–709.
7. Kemball-Cook D, Stephenson R. Lessons in logistics from Somalia. *Disasters.* 1984;8(1):57–66.
8. Ray J. A multi-period linear programming modal for optimally scheduling the distribution of food-aid in West Africa[D]. Knoxville: University of Tennessee; 1987.
9. Rathi AK, Church RL, Solanki RS. Allocating resources to support a multicommodity flow with time windows. *Logis Transport Rev.* 1993;28(2):167–88.
10. Dror M, Laporte G, Trudeau P. Vehicle routing with split deliveries. *Discrete Appl Math.* 1994;50(3):239–54.
11. Fiedrich F, Gehbauer F, Rickers U. Optimized resource allocation for emergency response after earthquake disasters. *Saf Sci.* 2000;35(1):41–57.
12. Özdamar L, Ekinci E, Küçükyazıcı B. Emergency logistics planning in natural disasters. *Ann Oper Res.* 2004;129(1–4):217–45.
13. Tzeng GH, Cheng HJ, Huang TD. Multi-objective optimal planning for designing relief delivery systems. *Transport Res Part E: Logis Transport Rev.* 2007;43(6):673–86.
14. Bektas T. The multiple traveling salesman problem: an overview of formulations and solution procedures. *Omega: Int J Manag Sci.* 2006;34(3):209–19.
15. Malik W, Rathinam S, Darbha S. An approximation algorithm for a symmetric generalized multiple depot, multiple travelling salesman problem. *Oper Res Lett.* 2007;35(6):747–53.
16. Carter AE, Ragsdale CT. A new approach to solving the multiple traveling salesperson problem using genetic algorithms. *Eur J Oper Res.* 2006;175(1):246–57.
17. Ekici A, Keskinocak P, Swann JL. Modeling influenza pandemic and planning food distribution[J]. *Manuf Serv Oper Manag.* 2014;16(1):11–27.
18. Chen W, Guinet A, Ruiz A. Modeling the logistics response to a bioterrorist anthrax attack. *Eur J Oper Res.* 2016;254(2):458–71.
19. Ren Y, Fernando, Wu S. Optimal resource allocation response to a smallpox outbreak. *Comput Ind Eng.* 2013;66(2):325–337.
20. He Y, Liu N. Methodology of emergency medical logistics for public health emergencies. *Transport Res Part E: Logis Transport Rev.* 2015;79:178–200.
21. Liu M, Zhang Z, Zhang D. A dynamic allocation model for medical resources in the control of influenza diffusion. *J Syst Sci Syst Eng.* 2015;24(3):276–92.
22. Liu M, Zhang D. A dynamic logistics model for medical resources allocation in an epidemic control with demand forecast updating. *J Oper Res Soc.* 2016;67(6):841–52.
23. Anparasan A, Lejeune M. Resource deployment and donation allocation for epidemic outbreaks. *Ann Oper Res.* 2017;259(6):1–24.
24. Büyüktaktakın İE, Des-Bordes E, Kızı EY. A new epidemics-logistics model: insights into controlling the Ebola virus disease in West Africa. *Eur J Oper Res.* 2018;265(3):1046–63.
25. Dasaklis TK, Rachaniotis N, Pappis C. Emergency supply chain management for controlling a smallpox outbreak: the case for regional mass vaccination. *Int J Syst Sci Oper Logis.* 2017;4(1):27–40.

26. Rachaniotis N, Dasaklis TK, Pappis C. Controlling infectious disease outbreaks: a deterministic allocation-scheduling model with multiple discrete resources. *J Syst Sci Syst Eng.* 2017;26(2):219–39.
27. Dasaklis TK, Pappis CP, Rachaniotis NP. Epidemics control and logistics operations: a review. *Int J Prod Econ.* 2012;139(2):393–410.
28. McCormick GP. Computability of global solutions to factorable nonconvex programs: part I—convex underestimating problems. *Math Program.* 1976;10(1):147–75.
29. Shang J, Yildirim TP, Tadikamalla P, et al. Distribution network redesign for marketing competitiveness. *J Mark.* 2009;73(2):146–63.