Logistical aspects when coping with non-pandemic biological terror attack

Irit Talmor
Sir Harry Solomon School of Management, Western Galilee College, Akko, Israel

Received 16 February 2019
Revised 17 July 2019
21 September 2019
Accepted 4 October 2019

Abstract

Purpose – This paper aims to examine the time it would take to provide medical prophylaxis for a large urban population in the wake of an airborne anthrax attack and the effect that various parameters have on the total logistical time.

Design/methodology/approach – A mathematical model that evaluates key parameters and suggests alternatives for improvement is formulated. The objective of the model is to minimize the total logistical time required for prophylaxis by balancing three cycles as follows: the loading cycle, the shipping cycle and the service cycle.

Findings – Applying the model to two representative cases reveals the effect of various parameters on the process. For example, the number of distribution centers and the number of servers in each center are key parameters, whereas the number of central depots and the local shipping method is less important.

Research limitations/implications – Various psychological factors such as mass panic are not included in the model.

Originality/value – There are few papers analyzing the logistical response to an anthrax attack, and most focus mainly on the strategic level. The study deals with the tactical logistical level. The authors focus on the distribution process of prophylaxis and other medical supplies during the crisis, analyze it and identify the parameters that influence the time between the detection of the attack and the provision of effective medical treatment to the exposed population.

Keywords Supply chain, Bioterrorism, Flexibility versus availability, Medical response planning, Anthrax

Paper type Research paper

Introduction

The danger posed by biological terrorism, particularly the use of anthrax was dramatically demonstrated in the fall of 2001 when letters containing dry anthrax spores were sent through the US mail system, infecting 22 individuals and leading to five deaths (Inglesby *et al.*, 2002). While considerable attention has been paid to issues such as the dispersal of anthrax plumes, the number of people expected to be infected by these plumes and the need for a rapid medical response, less attention has been paid to the tactical logistical

This research was begun while the author was a Post-Doctoral Fellow at the Center for International Security and Cooperation at Stanford University. I want to thank Professor Dean Wilkening for his supervision and valuable contribution to this study.

arrangements required to provide a rapid medical response to such an attack (Brookmeyer *et al.*, 2003; Craft *et al.*, 2005; Hupert *et al.*, 2007; Hupert *et al.*, 2009; Wein *et al.*, 2003).

This paper presents a mathematical model to assess the efficacy of various logistical options based on the number of medical distribution centers, the arrangements for processing individuals at each site including the number of stations set up for triage, medical examinations and the dispensing of drugs and the number of medical personnel available to staff these stations for a given size urban area. We will examine the optimal medical distribution system as a function of the number of people who require treatment in the wake of a bioterrorism event. We will consider both the size of the exposed population and the number of individuals needing preventive measures, even if they were not exposed.

All, biological pathogens incubate for a period of days to weeks in their hosts. This fact gives rise to the possibility that an effective defense against biological attacks can be developed based on rapid medical intervention. Medical treatment of exposed individuals can prevent the outbreak of disease, for those diseases for which medical treatment is available if it is administered before an individual develops symptoms or early in the symptomatic phase of the illness. For inhalation anthrax in humans, the incubation period is estimated to be between one and six days, which is relatively short compared to many other biological agents (Wilde, 1998; Wilkening, 2008). However, the incubation period may be much longer (up to approximately 40 days), if a significant fraction of the population is exposed to low doses of the disease, as will likely be the case because most disease incubation periods are dose-dependent (Franz *et al.*, 1997). For inhalation anthrax, treatment for 60 days, and possibly longer with antibiotics (ciprofloxacin, doxycycline or penicillin; possibly in combination) and other antimicrobial drugs, perhaps, followed by vaccination, should prevent the outbreak of disease in a large percentage of the exposed population (Hupert *et al.*, 2009; Wilde, 1998). In fact, much medical personnel assumes that the efficacy of antibiotics can approach 100 per cent, if the treatment begins soon enough.

The fact that anthrax is a non-contagious agent makes it much easier to treat because the disease cannot spread from person to person. This fact makes it much easier to create "points of dispensing" (PODs) for distributing antibiotics because one does not have to worry about quarantine procedures or contact tracing to uncover secondary exposures from infected individuals. Only the population in the area exposed to the anthrax plume would need to be treated, along with any other individuals concerned about having been exposed (whether these fears are valid or not).

The most important factor in post-attack medical intervention is the speed with which treatment can be delivered. Reaching a very high percentage of the exposed population is the next most important factor. Finally, the efficacy of intensive hospital care for those individuals who do become ill is also important. However, the number of people seeking intensive medical care depends greatly on the effectiveness of the first two factors. Indeed, a medical response strategy that relies heavily on hospital care is certainly less preferable because of its implications.

The ability to treat exposed individuals before they become symptomatic depends on the time delay between the initial release and the point at which the authorities recognize that an attack has occurred (detection time) and the speed with which medical treatment can be delivered to the exposed population. This speed depends, in turn, on three main factors as follows. The first factor is how long it takes to airlift medical supplies from a central location to local staging sites at airports in the vicinity of the exposed population. The second factor is the speed with which these supplies can be distributed to local PODs. The third factor is the time it takes to process people at these PODs.

Literature review

Models that deal with locating facilities and allocating resources to these facilities exist in both the civilian and military contexts. In the civilian context, the focus is typically on long-term considerations of supply chain management. The benefits of choosing a certain facility are assessed mainly by its long-term operating costs and benefits, not by the initial setup costs, which typically are short-term. This issue has been analyzed extensively in many fields – from warehouses and depots through power stations up to optimal locations of charging stations for electric cars (Barz, Buer and Haasis, 2016; Blelloch and Tangwongsan, 2010; Canel and Khumawala, 2001; Cui, Zhao and Zhang, 2018; Gourdin *et al.*, 2000; Heyns and van Vuuren, 2018; Love *et al.*, 1988; Luo and Yang, 2016; Ravi and Sinha, 2006; Zhang *et al.*, 2018).

In the military context, the classical dilemma involved in deciding on the structure and location of logistic resources for operational forces is flexibility versus availability. More flexibility is achieved when logistic resources are concentrated at higher hierarchal levels and allocated down to lower levels according to developing circumstances. The allocation process takes time because of physical obstacles such as distance and conceptual obstacles such as missing, partial or delayed information. Thus, supplies may be less available when they are most needed. Greater availability is achieved when resources are decentralized among lower hierarchical levels in advance. Such a strategy enables the commanders to deal with uncertainty under changing circumstances, but at the cost of inefficient use and increased expense (Badea and Petrisor, 2012; Davids *et al.*, 2013; Gallasch *et al.*, 2008; Gamez, 2015; John and Schultz, 1991; Johnson and Coryell, 2016; Kovács and Tatham, 2009; Kress, 2016; Mendershausen, 1958).

In the situations described above, the parameters and schedules are known or can be estimated. Thus, the number and location of the supply depots can be decided and stocked in advance. However, in the event of an anthrax attack, the situation is almost entirely different. It involves immediate, short-term considerations, which are the only ones that are relevant in this case. Responding to a bioterrorist attack is a one-time operation executed under emergency circumstances, strict time limitations and a high degree of uncertainty. The defender tries to protect civilians within boundaries that are either fuzzy or inexistent, while the timing of the attack is also vague.

Logistic preparations for this situation can be categorized into three levels as follows. First, at the strategic level, planners must organize, train and equip the forces that will have to cope with a bioterrorist attack. Second, at the operational level, the requirements associated with various biological attack scenarios including the supplies needed and the protocols for responding to possible situations are addressed. Third, at the tactical level, the process itself – distributing the medications, setting up and operating the PODs, and treating infected people – is carried out.

There is extensive discussion in the literature of these three logistic levels in the context of humanitarian responses to disasters (Leiras *et al.*, 2014 for a literature review, as well as Franke *et al.*, 2011; Rackham and Kelly, 2018; Wang *et al.*, 2015). On the other hand, studies that discuss bioterror events are much fewer and usually focus only on the first two levels. These studies use various models that analyze the preferred response (Caunhye and Nie, 2018; Perry *et al.*, 2018), estimate the number of deaths and the capacities of hospitals (Stone *et al.*, 2018) or analyze vaccination policies in the case of a smallpox outbreak (Bozzette *et al.*, 2003; Wanying *et al.*, 2016). There are even fewer papers that analyze the logistic response to an anthrax attack. Wanying *et al.* (2016) propose a detailed mathematical model for this challenge that considers the dynamics of the disease, assuming the number of distribution centers and their capacities are given in advance.

Our study deals with the tactical logistic level. We do not examine the detection problem, information flow or the efforts after the attack to replenish stockpiles. Instead, we focus on the process of distributing medical supplies during the crisis, analyze it and point out the parameters that influence the time interval between the detection of the attack and the effective medical treatment of the exposed population. While we are aware that no model can represent the real world adequately, we use our model to demonstrate the tension between flexibility and availability that exists, as well as the tension between centralization and decentralization that should be considered when planning for disaster response.

Methodology

Medical treatment

For mass casualty settings, post-exposure treatment with oral antibiotics is the only practical approach. Ciprofloxacin and doxycycline are the preferred antibiotics. For adults, the recommended ciprofloxacin dose is 500 mg twice daily and for doxycycline 200 mg doses twice daily. Simultaneous treatment with multiple antibiotics and antimicrobial drugs following a bioterror incident is recommended to guard against drug resistant strains. Antibiotic treatment of inhalation anthrax should continue for at least 60 days. If an anthrax vaccine is available, post-exposure vaccination is recommended to guard against the recurrence of the disease after antibiotics are discontinued. The strategy for treating other population groups such as children and pregnant women is similar, with the necessary adjustments in dosages.

The model's rationale

The rationale behind the model is to supply antibiotic treatment as rapidly as possible to as many people as possible because doing so is the key element for reducing the rate of hospitalization and the number of casualties because of the attack. To achieve this goal, we suggest the following strategy. First, supply a seven day dose of antibiotics to individuals the first time they visit a POD. Second, complete the remaining 53-day treatment and subsequent vaccination later during the first week. Our model focuses on the first stage only, meaning analyzing the initial treatment distribution. We do not analyze other important, but less urgent issues such as vaccination or medical support that requires hospitalization.

The treatment distribution process begins at local airports near the contaminated area. Large cargo containers of medical supplies that have been shipped from the central location will be unloaded and rearranged into batches called push packs. These batches will be distributed among the PODs and their contents will be supplied to individuals.

At the next stage, the process splits into many sub-processes that are executed in parallel. Each sub-process contains three cyclical actions as follows: loading the medical supplies, shipping them and providing service to the population. The loading cycle is defined as the time required for loading batches of supplies on vehicles that will transport them to all PODs. The shipping cycle is defined as the time required to ship these supplies to the PODs. The service cycle is defined as the time required to distribute one batch of the supplies (a batch contains antibiotics for many people).

Assuming that each POD starts operating as soon as it receives the first batch and that cycles repeat until the entire population receives its initial dose of antibiotics or until supplies run out, the course of the process is likely to behave as demonstrated in Figure 1.

Each of the three cycles is executed using relevant resources and measured by the time required to complete one cycle. Loading uses forklifts and light trucks. Shipping uses the road infrastructure. Service uses features of the servers. We refer to these resources as the

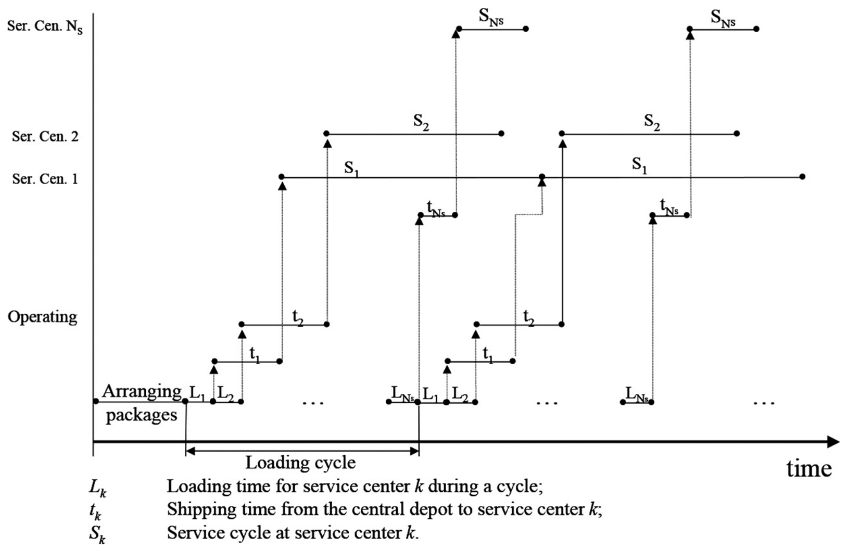

Figure 1.
Demonstration of the logistic process

independent (decision) variables. Note that there are two more types of decision variables that are common to all three actions as follows: the number of PODs operating and their locations.

Intuitively, it may seem better to open as many centers as possible to reduce the number of people being serviced at each center. This strategy has clear benefits for the population: reducing lines and waiting times, reducing driving time to a nearby POD, preventing congestion, and perhaps, even reducing the immediate psychological effects. Nevertheless, before adopting this strategy, two aspects related to the tension between flexibility and availability should be considered.

First, the strategic aspect needs to be taken into account. The more PODs that need to be opened, the more infrastructure, equipment, supplies and personnel required. This approach implies that more money and a larger budget must be spent on these preparations. Second, the tactical aspect must be considered. Increasing the number of PODs also increases the loading cycle times while reducing the service cycle, and vice versa. These opposing trends are illustrated in Figure 2.

The model

This section describes the major concepts and variables in our model. A detailed mathematical formulation is provided in Appendix 1.

Objective

The goal of the model is to minimize the logistic time. Logistic time is the duration of the process demonstrated in Figure 1, namely, the time from the beginning of packages' arranging until the end of the distributing of antibiotics (for seven day treatment). Note that reducing the logistic time is equivalent to increasing the average treatment rate; thus, minimizing the first is actually maximizing the other.

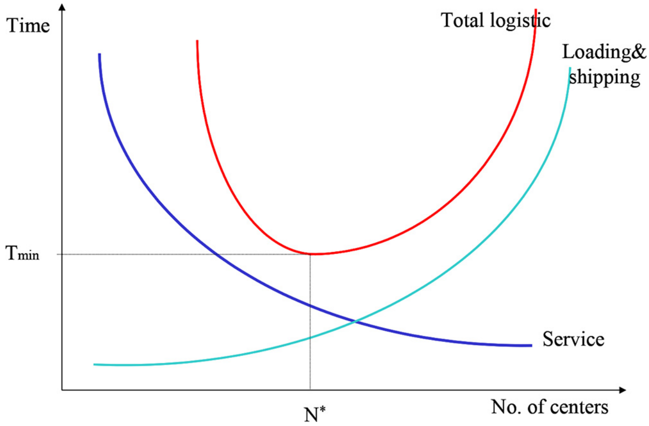

Figure 2.
Total logistic time as a function of the number of centers

Decision variables

The decision variables analyzed in the model are:

- the means such as the forklifts used for unloading and re-arranging the push packs at the local airport;
- the means of transport including surface vehicles such as transporters and trucks and aerial vehicles such as helicopters;
- the number and location of the PODs; and
- the number of servers in each center and the service rates

Parameters

The parameters of the model are grouped to represent different aspects of the problem, as follows:

Area characteristics

Airborne anthrax plumes can extend for long distances and contaminate several urban areas, each with its own unique characteristics. Two parameters are used in the model to characterize each region: its dimensions and population density. These parameters play a role in optimizing the process.

Loading phase

We assume that the loading is performed using several forklifts, with each truck being loaded by one forklift. The forklifts are identical, as are the trucks. The more forklifts used, the shorter the loading cycle time. Nevertheless, the decrease is not linear but concave because of mutual disruptions and stochastic elements that occur in all large-scale non-automated processes.

The loading rate is dictated by the volume of the package rather than its weight. A typical ciprofloxacin package for the seven-day treatment of 10,000 people is not very heavy. As mentioned, a loading cycle is defined by loading one truck for each activity center. Thus, the number of loading cycles is determined by dividing the volume of the supplies needed in a center by the truck's volume. To summarize, the parameters used in this phase are the number of forklifts, the loading rates and the capacity of the truck.

Shipping cycle

Shipping supplies from the depot at the local airport to the PODs can be done by ground (trucks or vans) or by air (helicopters). Generally, the transit time is the sum of three components as follows: the amount of time from leaving the point of origin to entering a freeway, the time on the freeway and the time from leaving the freeway until reaching the destination. The first and third components are short in distance but performed at low speed and under restricted conditions, whereas the second part is relatively long distance but typically done at higher speed, depending on traffic conditions. The same elements apply when analyzing air transportation with the components involved is taking off, flying and landing.

For ground transportation, we assume that the first and the third legs take 15-20 min. The duration of the second leg depends on distance and road conditions. Road conditions are characterized by two parameters, each with three levels. The first parameter is road quality, which can be good, moderate or poor. The second parameter is traffic flow, which can be free, constrained or jammed.

Service phase

We assume that centers operating in a specific region are similar in that they serve approximately the same number of people and have approximately the same number of servers. The service procedure is standard: there are several servers who supply antibiotics to people who come to the center. Each patient is treated by one server (the phrase "one server" is generic and can refer to a group of personnel that is required to serve one patient). The features of the servers are identical and so are the features of the people being served.

The service cycle time is determined by multiplying the aggregate service rate by the size of the batch, meaning the number of doses on a truck. If the result is greater than the loading cycle time, new supplies will arrive before all of the current supplies are distributed. In that case, the service phase is executed continuously. However, if the service cycle time is shorter than the loading cycle time, there will be idle periods between the successive arrivals of the trucks. Figure 1 illustrates this scenario. The service in center No. 1 goes on continuously and an inventory of medical supplies accumulates, whereas in center No. 2 there are idle times while waiting for supplies to arrive. Although one might think that the ideal situation occurs when the service cycle time does not exceed the loading cycle time, in the current situation the opposite is true. Continuous service prevents panic and stress among waiting patients, who may interpret the pause in service as being caused by a shortage of medical supplies. To summarize, the parameters in the service phase are the rate of service and the number of servers or their density relative to the population.

In next sections, we assess the model using two test cases. The parameters of the first example are virtual, whereas some parameters of the second example are taken from the real world.

Example 1: a virtual demonstration of the model

Basic data

The contaminated area is 15 km downwind with a ±10 km crosswind. The population density is 1,000 people/km^2. The loading rate is 5 min per 1 m^3. The service time for the distribution of the antibiotic is assumed to be 5 min per person, and a single server operates each POD. A forklift is used to organize medical packages and load them on light trucks, each with a 7 m^3 capacity. For ground transportation, we assume that the average speed on the freeways is 70 km/h and the first and third legs of the trip take 15-20 min each.

Results

The loading time, service time and the total logistic time as a function of the number of centers are shown in Figure 3. Providing one server per center leads to a minimal value of 97 h to complete the logistic process and is achieved by setting up and operating 543 centers.

Two interesting facts emerge from this simple example. The first is the amount of time involved in loading and shipping the medicine. This time increases steeply when only a few centers are operating, remains constant as long as a few tens of centers are operating and increases linearly with larger numbers of centers. The explanation for this phenomenon is simple. When only a few centers exist, each truck is filled up and more than one cycle is required. Thus, the loading cycle is the number of centers multiplied by the time required to load the trucks. When many centers are operating (more than 50, in this example), the total supply volume for each center does not exceed 1 m^3. Therefore, only one cycle is required. As a result, the loading cycle is the number of centers multiplied by the minimal loading constant. The in-between case occurs when the volume loaded on each truck is more than the minimal volume but less than its capacity. In this case, the loading cycle is independent of the number of centers but equals approximately the total volume of the supply required to treat all of the exposed population divided by the loading rate.

The second fact is the robust pattern of the total logistic function around the optimum. Adding or subtracting 100 centers (18 per cent) changes the optimum logistic time by less than 5 per cent.

Extension

According to the optimal results of the model, the density of servers should be equal to 1.81×10^{-3} (543 servers divided by the total population in the contaminated area). We ran

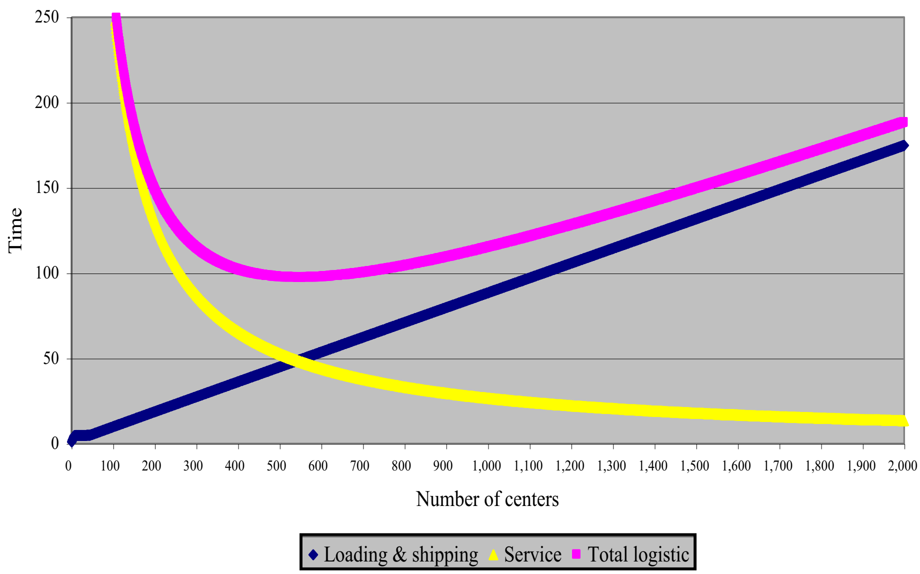

Figure 3.
Phases and total time required for logistics as a function of the number of PODs – one server per center

the model again, this time without specifying the number of servers per center in advance. Instead, we used the calculated density of the servers. This additional degree of freedom improved the results substantially. The optimal total logistic time declined from 97 to 62 h (35 per cent), with only 45 centers operating, each with 12 or 13 servers.

The total time required for the logistics, illustrated in Figure 4, exhibits a saw-tooth structure. This outcome occurs because, for any given number of centers, the duration of the service phase is derived from the most restricted centers, which, in our model are those that have a minimal number of servers. Initially, servers for new centers are allocated from those that have a number of servers above the minimum. As fewer people are served in each center, the service time is reduced and so is the total logistics time. This outcome repeats until a threshold point is crossed, and the number of servers in one or more centers falls below the previous minimum, causing the service time (and the total logistics time derived from it) to increase sharply.

This saw-tooth phenomenon suggests that searching for the optimum option is complicated because there are numerous local optimum points as opposed to one unique optimum solution. In real-life cases, the situation can become even more complex, as suggested in the next example.

Example 2: An anthrax aerosol attack in a major city in the USA

Basic data

The characteristics of the area in this example come from Wein *et al.* (2003). The contaminated area is 200 km downwind with a ±18 km crosswind. The closest community 30 km downwind is an urban area with a population density of 10,000 people/km^2, and the furthest community downwind is a rural area with a population density of 100 people/km^2. The service time for antibiotic distribution is between 0.12 (two shifts) and 0.18 (three shifts) per min. We assume that 10 forklifts are used to load the medical supplies on light trucks, each with a 7 m^3 capacity. Based on empirical studies that investigate the changes in average speed along freeways during the day, we use transport speeds of 50, 35 and 20 mph for free, constrained and jammed traffic, respectively. We also assume that the reduction in

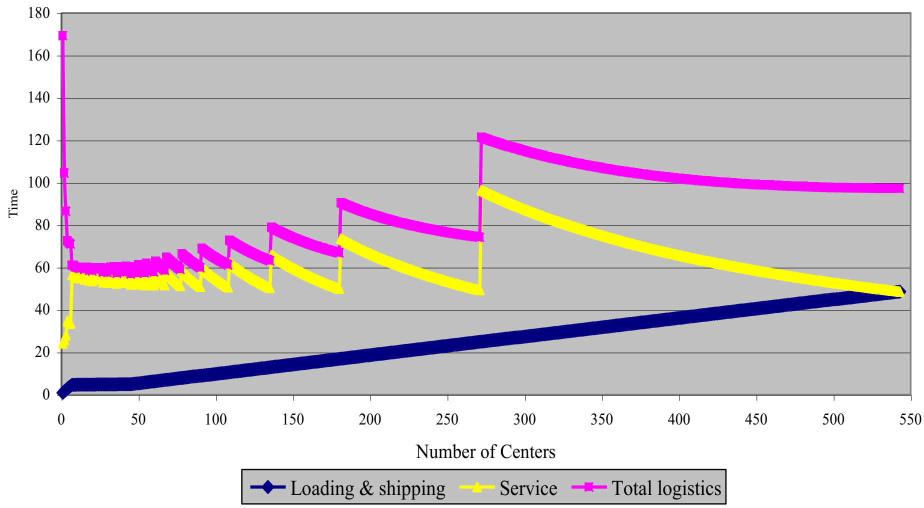

Figure 4.
Phases and total logistics time as a function of the number of PODs with a constant number of servers

average speed caused by road quality is 25 and 50 per cent for moderate and poor roadways, respectively.

Results

When both the number of servers and the number of centers are unlimited, the minimum time to complete the process is around 20 h for 200 servers per 1,000 people, operating 39 and 75 centers in the urban and rural regions, respectively. This outcome implies a total of approximately 2.4×10^6 servers, which is an impractical result. However, the total distribution time has a very broad minimum, suggesting that the number of servers can be reduced substantially without increasing the distribution time too much. Figure 5 shows that the density of the servers can be reduced to approximately 20-30 per 1,000 people without altering the total service time by more than 5-10 h.

When using more realistic server densities, we obtain the results shown in Figure 6. As the figure shows, the optimum number of PODs is independent of the density of the servers. However, the total logistics time drops monotonically as the server density increases. Table I presents the results for medical personnel with a density of 1.21×10^{-3} (Wein *et al.*, 2003).

For this density of servers, (1.21×10^{-3}) changing the number of centers has only a minor effect on the total logistic time (Figure 7). Any combination of centers in the ranges [232, 1,866] in the urban region and [14, 148] or [156, 185] in the rural region will lead to a total logistic time that is less than 140 h.

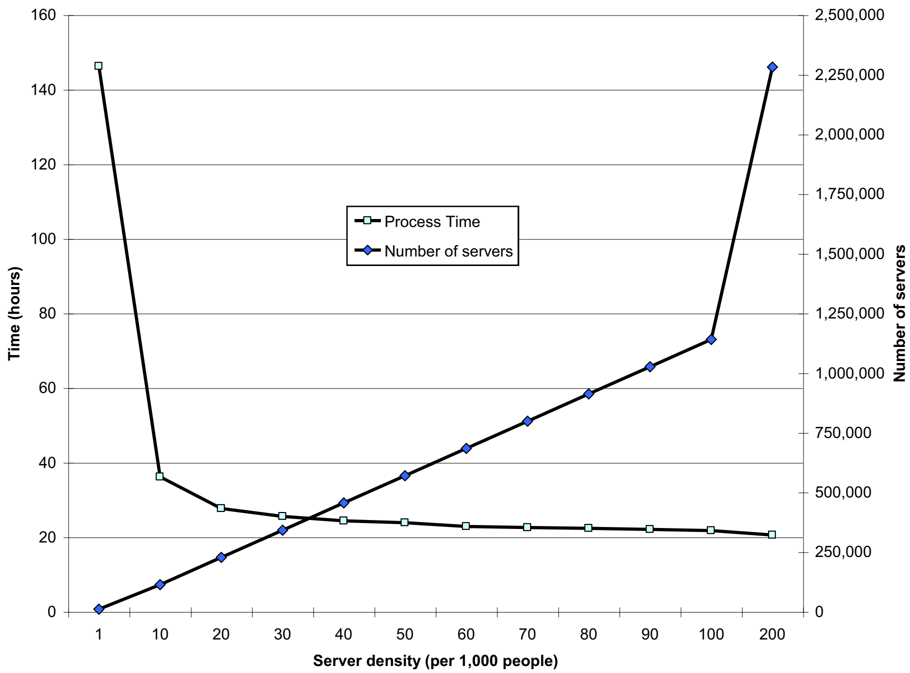

Figure 5. The logistics time and the number of servers as a function of density of servers and the number of centers in the urban region

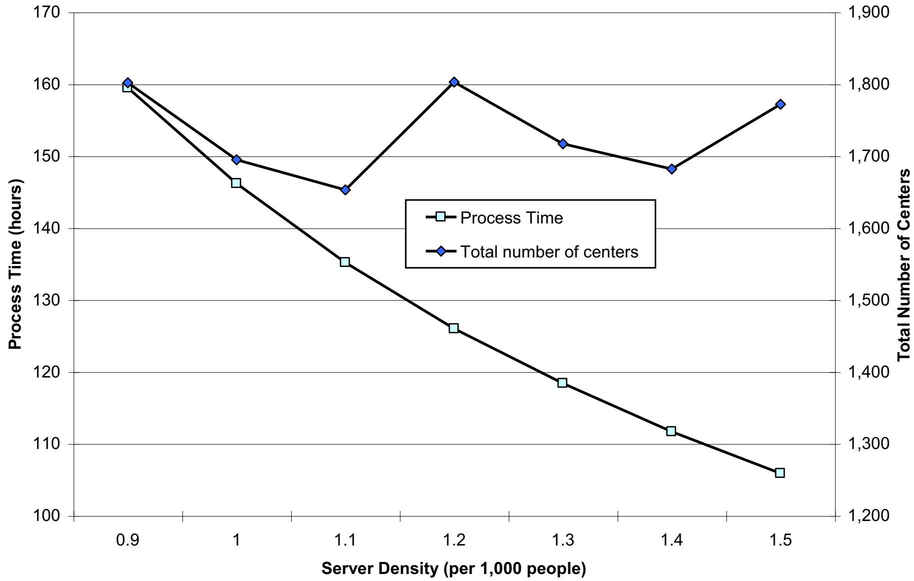

Figure 6.
Amount of time to process people and number of centers as a function of the density of the servers

Table I.
Results for a fixed density of servers (1.21×10^{-3})

Region	No. of centers	No. of cycles	No. of servers per center
Urban	1,451	1	9*
Rural	185	1	4**
Total	1,636	***	13,808

Notes: Time to complete the process is estimated at 125 h (5 days). * A few centers have 10 servers. ** A few centers have 5 servers. *** 1,636 trucks needed, less than 2 m^3 of each truck are used

Sensitivity analysis

We analyzed the influence of several parameters on the results as follows: service rate, number of forklifts, number of central depots, road quality and traffic conditions. The results are summarized in Table II. The total logistic time is affected mainly by the service rate. The number of forklifts has a relatively minor effect. Opening two central depots instead of one have a moderate effect on the results. Worsening road quality and traffic conditions have the same influence, although in the opposite direction. As mentioned above, the optimal number of centers is insensitive to any of these changes.

The efficacy of the medical intervention is maximized when the exposed population can receive treatment prior to symptoms appearing in it. Symptoms will likely begin to show within 48 h after exposure. Therefore, if antibiotic treatment can occur within 48 h after exposure to inhaled anthrax, the efficacy of medical intervention should be quite high. As shown above, the key parameters that affect service time are the density of the servers and the service rate.

Different combinations of these two parameters that meet the 48 h criterion are shown in Figure 8.

Thus, if one has 1.21 servers for every 1,000 people, the service rate would have to be 0.71 people/min to service the entire population within 48 h. To accomplish this goal, the medical personnel would have to reduce the average service time to 1.4 min. If the service time

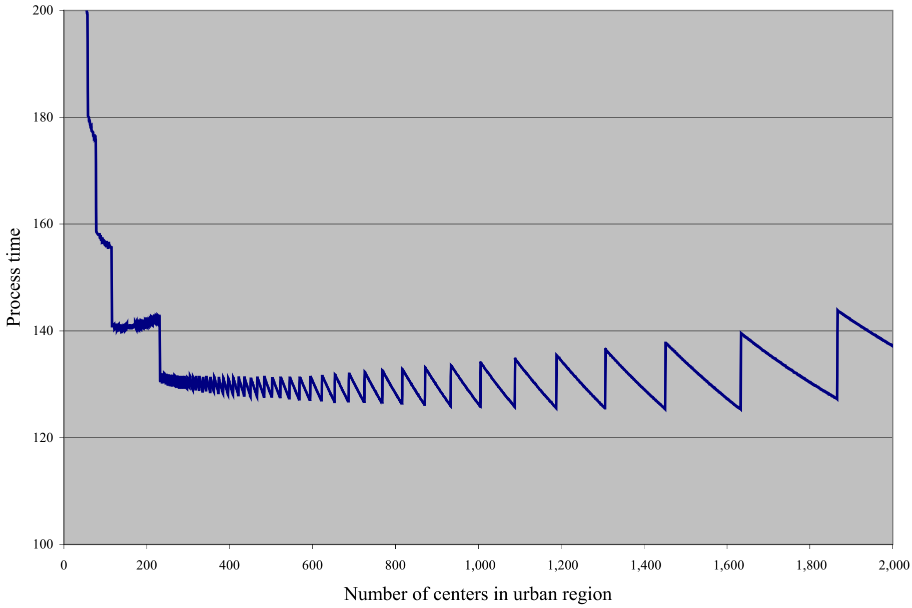

Figure 7. The process time as a function of the number of centers in the urban region (the number of centers in the rural area is 185)

Table II. Summary of sensitivity analysis

Parameter/variable	Change	Effect on total logistic time (%)	No. of PODs required
Basic case	–	125	1,636
Service rate	Improved by 20%	106 (−15%)	1,600
	Deteriorated by 20%	145 (+16%)	1,636
Number of forklifts	Improved by 20%	123 (−2%)	1,818
	Deteriorated by 20%	129 (+3%)	1,600
Number of central depots	2 instead of 1	118 (−6%)	1,817
Road quality and traffic conditions	Poor and jammed instead of well-maintained and free-flowing	134 (+7)	1,600

remained unchanged at 0.14 people/min, then the density of the servers should be 5 per 1,000 people to meet the 48 h criterion. This is four times the original density (1.21). In peacetime, only physicians can prescribe antibiotics and only medical or pharmaceutical personnel can administer them. However, in the aftermath of a bioterrorism event, these constraints may be relaxed to accelerate the antibiotic distribution process. One way of doing so is by using volunteers who do not have formal medical education but have received short basic training.

Such non-medical servers could provide antibiotics to people who, on the basis of an initial triage, do not have a medical history that would require more careful treatment. Included in this category are patients who are in good health, do not have any allergies to antibiotics and are not immune compromised. These individuals can be serviced in an "express lane" with only a brief explanation of how to use the antibiotics and what adverse reactions to watch for. Further explanations can be provided through the media, online and

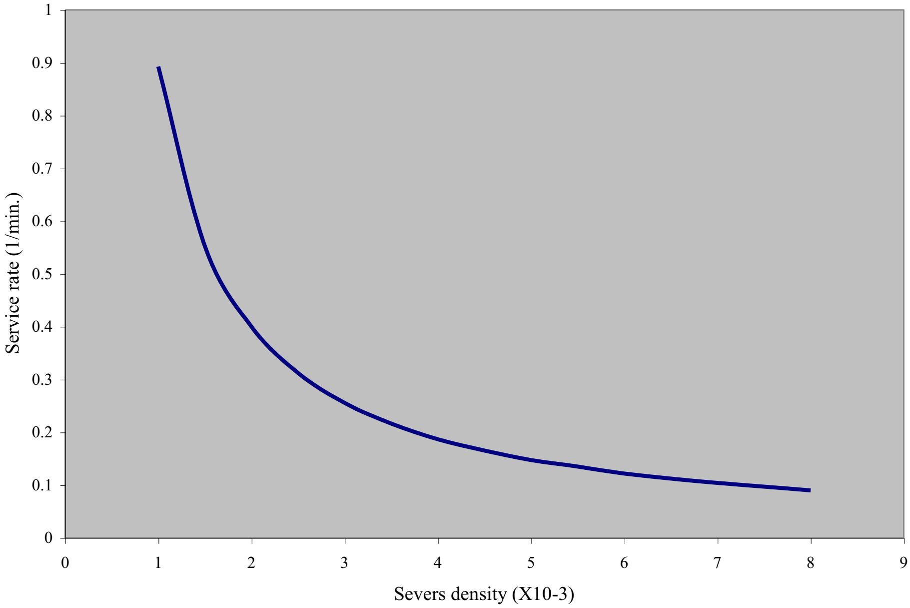

Figure 8. Combinations of server density and service rate that can reduce the total logistics time to 48 h (points that fall below the graph stand for total logistics time that exceeds 48 h)

through cell phones. People with more complex medical conditions will require professional servers such as paramedics, physician assistants, nurses or doctors. Moreover, the processing time for the special cases will be longer because of the need for more detailed medical histories. Thus, there are at least two service rates: a "fast" rate for medically simple cases and a "slow" rate for medically complex cases. Knowing the proportion of complex cases in the population and the ratio of the fast rate to the average rate allows one to determine the acceptable slow service rate (Appendix 2 for mathematical details).

Figure 9 illustrates the trade-off between the fast and slow service rates that will give the same value of the average service rate for different fractions of special cases in the exposed population: 0.1, 0.25 and 0.5. In this figure, the fast and slow service rates are measured in terms of the ratio with the average service rate. For example, if the fraction of special cases is 0.25 and the fast to average service rate ratio is 2, then the slow service rate can be reduced to 0.2 times the average rate without increasing the total logistic time.

Discussion and conclusions

This paper examines the time it would take to provide medical treatment for a large urban population in the wake of an airborne anthrax release, and the effect that various parameters have on the total time needed for the logistics to respond to this attack. While our model provides a means for determining the optimal service time, it often requires an unrealistic number of PODs and servers. Fortunately, because of its robustness, near optimal service times can be obtained with more realistic numbers for these parameters. Other variables such as the number of central depots, the local shipping method and the number of forklifts for loading supplies at the local airport have only minor effects on the results. The shipping can be done with small trucks, which are used extensively in everyday life.

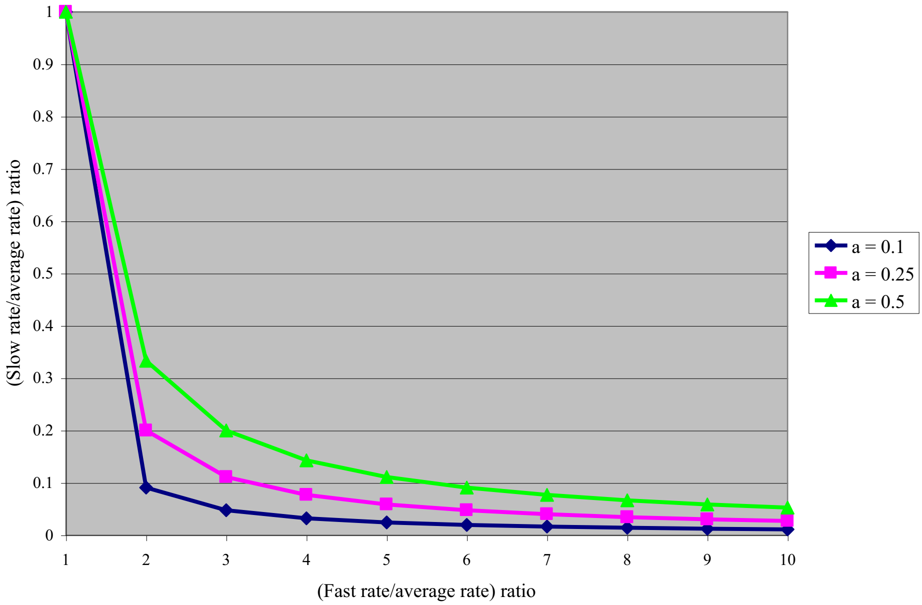

Figure 9.
The ratio of slow service rate to average service rate versus the ratio of fast service rate to average service rate, for various proportions of "special cases" in the population

The main bottleneck that affects the length of the process is the service rate. Thus, improving its efficiency is important. Several methods can be applied to do so. First, the authorities can provide information to the public using mass media together with tailored messages such as via cell phones or social media before and during their waiting in lines at the antibiotic distribution centers. The processing time can also be reduced significantly if the number of servers increases dramatically. When there is one server per individual, this means distributing the supplies prior to the attack. However, such a policy is not recommended because it has several serious drawbacks. The pre-distributed medications may have exceeded their shelf life. In addition, people may be tempted to use the antibiotics for other purposes, especially during flu season, raising the specter of increased antibiotic-resistant diseases.

The main focus of this model is to determine the number of PODs and the service rates required to provide rapid medical treatment to an exposed population in the wake of a bioterrorist event, given various uncertainties. However, before these results can be translated into real medical response plans, one must make sure that social or psychological factors such as mass panic and road congestion because of people fleeing the scene of the attack will not confound the smooth operation of the PODs discussed in this paper. Thus, securing both medical personnel and patients is very important, as is the dissemination of clear and accurate information to minimize panic or non-compliance with medical protocols. To some extent, these considerations can be partially reflected in the values of the parameters used in this analysis. This study opens up avenues for considering short-term costs when developing facility models. This idea will be developed in future research.

References

Badea, D. and Petrisor, S.M. (2012), "Military logistic basic approach as a system", *Land Forces Academy Review*, Vol. 17 No. 3, pp. 334-340.

Barz, A., Buer, T. and Haasis, H.D. (2016), "Quantifying the effects of additive manufacturing on supply networks by means of a facility location-allocation model", *Logistics Research*, Vol. 9 No. 1, pp. 1-14.

Blelloch, G.E. and Tangwongsan, K. (2010), "Parallel approximation algorithms for facility-location problems".

Bozzette, S., Boer, R., Bhatnagar, V., Brower, J., Keeler, E., Morton, S. and Stoto, M. (2003), "A model for a smallpox-vaccination policy", *New England Journal of Medicine*, Vol. 348 No. 5, pp. 416-425.

Brookmeyer, R., Johnson, E. and Bollinger, R. (2003), "Modeling the optimum duration of antibiotic prophylaxis in an anthrax outbreak", *Proceedings of the National Academy of Sciences*, Vol. 100 No. 17, pp. 10129-10132.

Canel, C. and Khumawala, B.M. (2001), "International facilities location: a heuristic procedure for the dynamic uncapacitated problem", *International Journal of Production Research*, Vol. 39 No. 17, pp. 3975-4000.

Caunhye, A.M. and Nie, X. (2018), "A stochastic programming model for casualty response planning during catastrophic health events", *Transportation Science*, Vol. 52 No. 2, pp. 437-453, doi: 10.1287/trsc.2017.0777.

Craft, D., Wein, L. and Wilkins, A. (2005), "Analyzing bioterror response logistics: the case of anthrax", *Management Science*, Vol. 51 No. 5, pp. 679-694.

Cui, S., Zhao, H. and Zhang, C. (2018), "Multiple types of plug-in charging facilities' location-routing problem with time windows for mobile charging vehicles", *Sustainability*, Vol. 10 No. 8, p. 2855.

Davids, C., Beeres, R. and van Fenema, P.C. (2013), "Operational defense sourcing: organizing military logistics in Afghanistan", *International Journal of Physical Distribution and Logistics Management*, Vol. 43 No. 2, pp. 116-133.

Franke, J., Widera, A., Charoy, F., Hellingrath, B. and Ulmer, C. (2011), "Reference process models and systems for inter-organizational ad-hoc coordination – supply chain management in humanitarian operations", *8th International Conference on Information Systems for Crisis Response and Management (ISCRAM 2011), May 2011, Lisbon, Portugal*.

Franz, D., Jahrling, P., Friedlander, A., Mcclain, D., Hoover, D., Bryne, W., Pavlin, J., Christopher, C.W. and Eitzen, E. (1997), "Clinical recognition and management of patients exposed to biological warfare agents", *Jama: The Journal of the American Medical Association*, Vol. 278 No. 5, pp. 399-411.

Gallasch, G., Lilith, E., Billington, N., Zhang, J., Bender, L. and Francis, A. (2008), "Modelling defence logistics networks", *International Journal on Software Tools for Technology Transfer*, Vol. 10 No. 1, pp. 75-93.

Gamez, A. (2015), "Logistics considerations for multinational operations", *Army Sustainment*, Vol. 47 No. 5, pp. 16-23.

Gourdin, É., Labbé, M. and Laporte, G. (2000), "The uncapacitated facility location problem with client matching", *Operations Research*, Vol. 48 No. 5, pp. 671-685.

Heyns, A.M. and van Vuuren, J.H. (2018), "Multi-type, multi-zone facility location", *Geographical Analysis*, Vol. 50 No. 1, pp. 3-31.

Hupert, N., Wattson, D., Cuomo, J. and Benson, S. (2007), "Anticipating demand for emergency health services due to medication-related adverse events after rapid mass prophylaxis campaigns", *Academic Emergency Medicine*, Vol. 14 No. 3, pp. 268-274.

Hupert, N., Wattson, D., Cuomo, J., Hollingsworth, E., Neukermans, K. and Xiong, W. (2009), "Predicting hospital surge after a large-scale anthrax attack: a model-based analysis of CDC's cities readiness initiative prophylaxis recommendations", *Medical Decision Making*, Vol. 29 No. 4, pp. 424-437.

Inglesby, T.V., O'Toole, T., Henderson, D.A., Bartlett, J.G., Ascher, M.S., Eitzen, E., Friedlander, A.M., Gerberding, J., Hauer, J., Hughes, J. and McDade, J. (2002), "Anthrax as a biological weapon, 2002: updated recommendations for management", *Journal of the American Medical Association*, Vol. 287 No. 17, pp. 2236-2252.

John, C. and Schultz, R.E. (1991), "Simulation modeling for military logistics and supportability studies", *Winter Simulation Conference Proceedings*, pp. 485-490.

Johnson, M. and Coryell, B. (2016), "Logistics forecasting and estimates in the brigade combat team: observer-coach trainers from the national training center provide methods for accurate, detailed logistics estimates", *Army Sustainment*, Vol. 48 No. 6, pp. 26-33.

Kovács, G. and Tatham, P. (2009), "Responding to disruptions in the supply network from dormant to action", *Journal of Business Logistics*, Vol. 30 No. 2, pp. 215-229.

Kress, M. (2016), *Operational Logistics: The Art and Science of Sustaining Military Operations*, Springer International Publishing.

Leiras, A., De Brito, I., Jr, Queiroz Peres, E., Rejane Bertazzo, T. and Tsugunobu Yoshida Yoshizaki, H. (2014), "Literature review of humanitarian logistics research: trends and challenges", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 4 No. 1, pp. 95-130, doi: 10.1108/JHLSCM-04-2012-0008.

Love, R.F., Morris, J.G. and Wesolowsky, G.O. (1988), *Facilities Location Models and Methods*, North-Holland, New York, NY.

Luo, X. and Yang, J. (2016), "Multiple coverage location problem of water emergency facilities in the Yangtze river", *International Journal of Simulation: Systems, Science and Technology*, Vol. 17 No. 36, pp. 9.1-9.6.

Mendershausen, H. (1958), "Economic problems in air force logistics", *The American Economic Review*, Vol. 48 No. 4, pp. 632-648.

Perry, I.A., Noe, R.S. and Stewart, A. (2018), "Use of medical countermeasures in small-scale emergency responses", *American Journal of Public Health*, Vol. 108 No. 3, pp. S196-S201.

Rackham, R. and Kelly, A. (2018), "Emergency planning and business continuity: why blood services must plan for both. How the EBA working group (WG) is assisting blood services", *Isbt Science Series*, Vol. 13 No. 1, pp. 51-58, doi: 10.1111/voxs.12386.

Ravi, R. and Sinha, A. (2006), "Approximation algorithms for problems combining facility location and network design", *Operations Research*, Vol. 54 No. 1, pp. 73-81.

Stone, K.W., Morehead, B.F., Karaye, I., Davis, C.M. and Horney, J.A. (2018), "Evaluating the effectiveness of a full-scale exercise of epidemiologic capacity for bioterrorism response", *Journal of Homeland Security and Emergency Management*, Vol. 15 No. 4, doi: 10.1515/jhsem-2017-0061.

Wang, L., Song, J. and Shi, L. (2015), "Dynamic emergency logistics planning: models and heuristic algorithm", *Optimization Letters*, Vol. 9 No. 8, p. 1533, doi: 10.1007/s11590-015-0853-z.

Wanying, C., Alain, G. and Angel, R. (2016), "Modeling the logistics response to a bioterrorist anthrax attack", *European Journal of Operational Research*, Vol. 254 No. 2, pp. 458-471.

Wein, L.M., Craft, D.L. and Kaplan, E.H. (2003), "Emergency response to an anthrax attack", *Proceedings of the National Academy of Sciences*, Vol. 100 No. 7, pp. 4346-4351.

Wilde, H. (1998), "Medical aspects of chemical and biological warfare", *Jama: The Journal of the American Medical Association*, Vol. 280 No. 13, p. 1199.

Wilkening, D.A. (2008), "Modeling the incubation period of inhalational anthrax", *Medical Decision Making*, Vol. 28 No. 4, pp. 593-605.

Zhang, B., Li, H., Li, S. and Peng, J. (2018), "Sustainable multi-depot emergency facilities location-routing problem with uncertain information", *Applied Mathematics and Computation*, Vol. 333, pp. 506-520.

Further reading

Coifman, B. (2002), "Estimating travel times and vehicle trajectories on freeways using dual loop detectors", *Transportation Research Part A: Policy and Practice*, Vol. 36 No. 4, pp. 351-364.

Coifman, B., Lyddy, D. and Skabardonis, A. (2000), "The Berkeley highway laboratory-building on the I-880 field experiment", *Proceedings of IEEE Intelligent Transportation Systems*, pp. 5-10.

Ren, Y., Ordóñez, F. and Wu, S. (2013), "Optimal resource allocation response to a smallpox outbreak", *Computers and Industrial Engineering*, Vol. 66 No. 2, pp. 325-337.

Wilson, J., Mckenzie, L., Mcleod, W., Darsey, D. and Craig, J. (2017), "Improving disaster response efforts through the development of a disaster health care response system", *Disaster Medicine and Public Health Preparedness*, Vol. 11 No. 5, pp. 600-604.

Appendix 1. Mathematical formulations

General

Let $x_j \sim Exp(\lambda)\ j = 1.m$ i.i.d.

Then,

$$\underset{j}{Min}(x_j) \sim Exp(m\lambda)$$

Thus, if there are m identical independent servers whose rate of providing service is distributed $Exp\ (\lambda)$ and n customers, the mean time until all customers are served is given by equation (1):

$$E(T) = \frac{1}{\lambda}\left[m(n-m+1) + \sum_{k=1}^{m-1}\frac{1}{k}\right] \tag{1}$$

Parameters

M = Number of zones in the contaminated area;
θ^i = Population density in zone i;
A^i = Size of zone i (km^2);
V = Truck capacity;
k = Number of forklifts;
$\boldsymbol{v}$ = 1-cubic meter loading rate;
ρ = Servers' density;
μ^i = Service rate for antibiotics in zone i; and
v = Average volume of one person's antibiotic dose.

Decision variables

N_s^i = Number of PODs (= number of trucks in a cycle) in zone i.

Functions

T_{Total} = Time required to complete the process;
T_L^i = One cycle's *loading* time referring to zone i;
T_D^i = Time required to transfer material from the central depot to the furthest POD in zone i;
T_S^i = Service time of a batch cycle in zone i;
N_c^i = Number of cycles in zone i;
Γ_L = Loading delay function;

Γ_S = Service delay function; and
S^i = Number of servers in a POD in zone i.

Then:

$$T_{Total} = \underset{i}{Max}\left\{T_L^i + T_D^i + \left(N_c^i - 1\right)\cdot Max\left(T_L^i, T_S^i\right) + T_S^i\right\} \tag{2}$$

Explanation: the process contains sub-processes that are executed in parallel for each POD – loading, transferring and servicing. The duration of each sub-process is the time to complete the first cycle of loading and transferring, plus the time to complete the last cycle of servicing plus the time to complete ($N_c^i - 1$) times the loading cycle or servicing cycle, which lay between them. Because these cycles in the sub-process are executed in parallel, we add only the longer one. The whole process is completed when the longest of all sub-process is completed.

$$T_L^i = \frac{\sum_i Min\left[V, Max\left(1 \ , \quad v\cdot\frac{\theta^i A^i}{N_s^i}\right)\right]}{M\cdot v}\cdot\left[\frac{Max\left(\sum_i N_s^i - k, 0\right)}{k} + \frac{1}{N_c^i}\sum_1^{k-1}\frac{1}{j}\right] + \Gamma_L \tag{3}$$

Explanation: the average loading time of the i-th POD is an implementation of equation (1) in our model: the multiplication of two expressions. The first is the volume that is loaded on a truck. The second is the expected loading time when k trucks are loaded at the same time. Note that both expressions are dependent on N_s^i, which is the decision variable. N_c^i is also dependent on N_s^i and its formulation is presented in equation (5). Γ_s is added to express the extra delay because of mutual interruptions. Its formulation is presented in equation (7).

$$T_S^i = \frac{Min\left(\frac{V}{\nu} \ , \quad \frac{\theta^i A^i}{N_s^i}\right)}{\mu^i}\cdot\left\{\frac{Max\left[Min\left(\frac{V}{\nu} \ , \quad \frac{\theta^i A^i}{N_s^i}\right) - S^i \ , \quad 0\right]}{S^i} + \frac{1}{N_c^i}\sum_1^{s-1}\frac{1}{j}\right\} + \Gamma_S^i \tag{4}$$

Explanation: the average servicing time of the i-th POD is also an implementation of equation (1) in our model: the multiplication of two expressions. The first is the estimated service time of a batch loaded on the truck for one server. The second is the number of servers that are operating at the same time. Note that both expressions are dependent on N_s^i, which is the decision variable. Γ_s is added to express the extra delay because of mutual interruptions. Its formulation is presented in equation (7).

$$N_c^i = \frac{1}{V}\cdot\frac{v\cdot\theta^i A^i}{N_s^i} \tag{5}$$

Explanation: the number of cycles is computed as the total volume to be loaded for the i-th POD divided by the truck's capacity. The volume to be loaded depends on the number of PODs.

$$\Gamma_L = 2^{\log\left(\sum_i N_s^i \cdot N_c^i\right)}\cdot\sqrt{\frac{\sum_i N_s^i\cdot N_c^i}{k}} \tag{6}$$

$$\Gamma_S^i = 2^{\log\left(\frac{\theta^i A^i}{N_s^i}\right)} \cdot \sqrt{\frac{\theta^i A^i}{S^i N_s^i}} \tag{7}$$

Explanation: the delays are affected by the number of PODs operating, and by the number of forklifts and servers used. These formulas were chosen to be non-linear concave functions.

$$S^i = \rho \cdot \frac{\theta^i A^i}{N_s^i} \tag{8}$$

Explanation: the number of servers in each POD is calculated as the density of the servers multiplied by the size of the population in the area.

Appendix 2. Define

μ = Average service rate;
k_1 = Ratio between fast service rate and average service rate ($k_1 \geq 1$);
k_2 = Ratio between slow service rate and average service rate ($k_2 \leq 1$); and
α = Proportion of complex cases in the population ($\alpha \leq 1$).

An approximation of the average service time is as follows:

$$\frac{1-\alpha}{k_1\mu} + \frac{\alpha}{k_2\mu} = \frac{1}{\mu} \tag{9}$$

After some algebraic manipulations, we get:

$$\alpha = \frac{k_2(k_1-1)}{k_1-k_2}$$

or

$$k_2 = \frac{\alpha k_1}{k_1-(1-\alpha)}$$

Corresponding author
Irit Talmor can be contacted at: iritT@wgalil.ac.il