# Research on emergency facilities location problem and its greedy dropping heuristic algorithm response to public health emergency

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**Abstract**

When a public health emergency, such as an anthrax attack, happens in many areas, it is vital to deploy the medical supplies to the affected people quickly. In this condition, emergency facilities, which provide medical supplies, play an important role in rescue management. The decision of where to locate the emergency facilities becomes very critical, as it determines the efficiency and effectiveness of the emergency management. In this paper, a multi-objective programming model that balances the total cost of emergency facilities and effect of rescue is proposed, and the effect of rescue is measured by the ratio of the arrival quantity of the rescue material to the demand. And then the model is solved by the Greedy Dropping heuristic after the multi-objective function is transformed into a single-objective. Finally, a practical example is given to illustrate the application of the model.

*Keywords:* Emergency facilities location problem, Public health emergency, Greedy Dropping Heuristic Algorithm, Rescue effect.

## 1 Introduction

In the past few years, a number of public health emergencies, such as, the anthrax-related exposures in Florida [1], the SARS in 2003, the pig flu in 2009, the H7N9 avian influenza in 2013, the Ebora virus in West Africa in 2014 have been witnessed by the world. In the event of these public health emergencies, a large amount of emergency materials should be provided to the exposed individuals to minimize the number of casualties [2]. In this condition, the emergency logistics network, which is made up of the points of dispensing, emergency centres, and replenishment sources should be established [3, 4]. In the emergency logistics network, the location of dispensing points, which provide medical supplies to the effected people, play an important role in rescue management. The decision of where to locate the dispensing points become very critical, as it determines the efficiency and effectiveness of the emergency management. As a result, the problem of locating dispensing points can be taken as the emergency facility location problems.

Facility location problems had been widely addressed in the literature. Daskin [5] and Drezner [6] defined that facility location problems deals with decisions of finding the best (or optimal) configuration for the installation of one or more facilities in order to attend the demand of a population. Larson [7-8] developed a set of spatial queuing models, which calculated the steady-state busy fractions of servers on a network once their positions had been specified. Orhan and Esra [9] formulated the MCLP in the presence of partial coverage and developed a solution procedure based on Lagrangean relaxation. Marianov and ReVelle [10] developed a model of queuing maximal availability location problem (Q-MALP) based on maximal availability location problem (MALP). But all of these models were within a deterministic framework. Daskin [11] presented the maximum expected coverage location problem (MEXCLP) in 1983, which was a current impetus to probabilistic facility location model. Chen and Lin [12], Snyder and Daskin [13] gave research on facility location problems with uncertainties, and then Snyder [14] proposed a complete review on facility location problems with uncertainties.

In recent years, the topic of emergency facility location has received substantial attention. According to Jia et al. [15], emergency facility location problems could be divided into three types depending on the objective function of the location models: covering models, *p*-median models, and *p*-centre models. And then Jia et al. [16] developed a new facility location model for the medical supply distribution for large-scale emergencies. Alminana and Pastor [17] presented the specialized set-covering formulations, and solved the formulations by branch and bound linear optimization. Fisher and Kedia

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[18] developed the Heuristics Algorithm for the solution of this problem. Hu, et al [19] formulated a mathematical model which integrates the traditional location selection models, such as the biggest cover mode, the *p*-center model and the *p*-median mode, and the principles of fairness and efficiency for the emergency center location were considered. Xi et al [20] developed a modified p-median problem model that accounts for rescue time limitations, and they developed a variable neighbourhood search- (VNS-) based algorithm for the model considered.

Although there many researches on normal facility location problems, there are a few of those on the location problem of emergency facility under the environment of diseases diffusion. Because of the special functions of emergency response system, some special requirement must be satisfied and the restrictions are more rigorous. Thus the traditional facility locations model can not solve the location problem of emergency facility. Some improvements on the original model are needed. The paper proposed a multi-objective programming model under the environment of diseases diffusion which balances the total cost of a rescue centre and the effect of rescue. The demand for the rescue materials is calculated by an indefinite integral, and the effect of rescue is measured by the ratio of the arrival quantity of the rescue material to the demand.

This paper is organized as follows. Model formulation is present in section 2. A Greedy Dropping Heuristic Algorithm is introduced in section 3. A numerical study is presented to illustrate the feasibility and effectiveness of this model in Section 4. Finally, concluding remarks are summarized in Section 5.

## 2 Model formulations

### 2.1 ASSUMPTIIONS

To smooth the progress of model formulation in the following subsections, five assumptions are postulated.

(1) The changes of needs for the emergency supplies on disaster areas are based on the proliferation of dangerous source, and they are on a function of time.

(2) In the period of decision-making, the dispensing point is set up in every time unit according to the demand of the affected area, and it is opened dynamically.

(3) Once the dispensing point is opened up, it will remain open in the subsequent period. As the cost of re-location and establishment of dispensing point (that is, the transfer cost) is very high;

(4) The dispensing point reserves limited emergency materials, but it should try all best meet all the needs of the disaster areas;

(5) The transportation cost of candidate dispensing point at the disaster area is of prior determination and it doesn't change according to time.

### 2.2 FORMULATION OF AN EMERGENCY FACILITY LOCATION MODEL

We consider a set *I* of demand points and a set *J* of eligible dispensing points in order to formulate the covering dispensing point location model for large-scale emergencies. And the mathematical formulation of the problem and the notation are given below.

Sets and parameters:

*h*, the maximal number of dispensing points that can be placed;

$f_{ij}$, the transporting cost every unit goods from eligible dispensing point *j* to demand point *i*;

$c_j$, the fix fee of establishing the dispensing points in the demand area *J*;

*C*, the total fee of establishing the dispensing points;

$o_j$, the fee for the maintenance of dispensing points *J* every year;

*O*, the total fee for the maintenance of dispensing points;

$I_j$, the total amount of emergency material at the *J* dispensing point

$a_{ijk}$, the amount of emergency rescue material from eligible dispensing points *j* to demand point *I* during the *k*th period;

$c_{ik}$, the total quantity of needed relief materials at the demand point *I* during the *k*th period;

*q*, the shortage cost of per unit emergency materials.

$x_j$ : If the dispensing point *J* is selected, $x_j$ =1; else $x_j$ =0, j=1, 2, *J*.

The objective aims at minimizing the total cost of emergency rescue system and maximizing the effect of rescue. So the double object function of dispensing point can be expressed as:

$$\min V = \sum_{j=1}^{J} c_j x_j + \sum_{j=1}^{J} o_j x_j + \sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{J} a_{ijk} f_{ij} + \sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{J} (c_{ik} - a_{ijk}) q \quad (1)$$

$$\max R(x) = \sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{J} x_j a_{kij} / \sum_{i=1}^{I}\sum_{k=1}^{k} c_{ik} \quad (2)$$

The objective function (1) aims at minimizing the total cost of the emergency system, and the total cost includes the transportation cost of the emergency materials, the fixed costs for the establishment of a new dispensing point, the total annual operating cost of every year, and the shortage cost. The objective function (2) targets on maximizing the effect of rescue which can be expressed by the ratio of the arrival quantity of the rescue material to the demand.

Subject to:

$$c_{ik} = \int_{t_k}^{t_{k+1}} c_{ik}(t)dt \tag{3}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K} a_{ijk} \le l_j \tag{4}$$

$$\sum_{j=1}^{J} a_{ijk} \le c_{ik} \tag{5}$$

$$\sum_{j\in J} x_j \le h \tag{6}$$

$$x_j = \{0,1\} \tag{7}$$

$$a_{ijk} \ge 0 \tag{8}$$

$$\sum_{j=1}^{J} c_j x_j \le C \tag{9}$$

$$\sum_{j=1}^{J} o_j x_j \le O \tag{10}$$

$$\sum_{i=1}^{I} c_{ik} \le \sum_{i=1}^{I}\sum_{j=1}^{J} x_j l_j \tag{11}$$

Constraint (3) states that the total quantity of relief materials are needed at the demand point I during the *k*th period, which can be calculated according to the spread discipline of dangerous source and the practical situation of every affected area. Constraint (4) restricts the amount of rescue materials supplied by every dispensing point. Constraint (5) shows that the needs on the rescue materials at every affected area should be less than the supply of emergency goods provided by the dispensing point. Constraint (6) is used to represent that there are at most *h* rescue centres to be located in a set *J* of possible locations. Facilities Location Model usually limits the number of rescue centres required in the demand area. Constraint (7) is the bound of decision variables. Constraint (8) restricts that the volume of emergency materials traffic are non-negative. Constraints (9) states that the fixed costs for the establishment of a new dispensing point do not exceed the estimated costs, and constraint (10) reveals that the total annual operating cost for the establishment of dispensing point do not excess the general estimated cost. Constraint (11) shows that the total quantity of needed relief materials should be less than the total stock of the selected dispensing point.

## 3 A Greedy Dropping Heuristic Algorithm

Generally speaking, the mathematical model of the multi-object programming can be described as:

$$\min V(x),\ \max Z(x)$$

$$X = \left\{x, x \in R^n, g_i(x) \le 0, h_i(x) = 0, x_j \ge 0, \forall i, j\right\}.$$

Where $x$ is n-dimensional vector variables, $V(x)$ and $Z(x)$ are the objective functions. $g_i(x) \le 0$ is the inequality constraint equation, and $h_i(x) = 0$ is the equality constraint equation. In the $n$-dimensional space, $m + n$ restrictive conditions and nonnegative constrains form a viable solution for *X*. domain. The multi-objective planning solution can be achieved through multi-objective planning into a single objective planning. The commonly used conversion methods are: weighted method, constraint method, Phillips linear multi-target, Xlieni linear multi-target methods, and so on.

For the single object programming model of facility location, the solving Algorithm is the accurate methods and the heuristic methods. And the accurate methods and the heuristic methods have the potential to generate efficient solutions to the considered facility location problem. However, the accurate methods do not provide information on how far the solutions are possibly away from optimality. In this section, we develop a heuristic method, which is called the Greedy Dropping Heuristic Algorithm, in addition to generating good solutions to the location problems, also provides bounds on the optimal objective value of the maximal covering location problem. The procedure of the Greedy Dropping Heuristic Algorithm is as follows.

Step1: initialization, setting the cycle variables $k = n$, selecting all the dispensing points, the demand point will be assigned to a dispensing point in accordance with the principle of minimum cost;

Step2: remove a dispensing point, which meets the following conditions: if it is removed and its clients are re-assigned, the augmenter of the total cost is the smallest. Then set $k = k\text{-}1$;

Step3: duplicate step2, until $k = p$.

Greedy heuristic algorithm does not necessarily get the optimal solution, but when the data volume is tremendous, the calculation speed will be relatively quick.

## 4 A case study

To illuminate the validity of the model, an example is introduced. Suppose that there are eight disaster areas which suffer from the measles, and three dispensing points will be set up to supply the emergency materials to the eight disaster areas. After inspections, there are five candidate dispensing points. The transport cost from dispensing point to demand point is indicated in Table 1. The cost and maximize storage of each dispensing point is shown in Table 2.

TABLE 1 Transport cost from dispensing point to each demand point

| area i / point j | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | 7 | 8 | 5 | 6 | 8 | 9 | 5 | 6 |
| 2 | 13 | 12 | 11 | 14 | 5 | 4 | 4 | 3 |
| 3 | 15 | 16 | 12 | 12 | 6 | 5 | 7 | 12 |
| 4 | 4 | 6 | 5 | 4 | 14 | 12 | 11 | 15 |
| 5 | 6 | 7 | 5 | 6 | 4 | 3 | 4 | 6 |
| 6 | 5 | 6 | 11 | 15 | 8 | 12 | 15 | 17 |

TABLE 2 Cost of establishment and maintenance for each dispensing point

| Point j | $c_j$ | $o_j$ | $l_j$ |
|---|---|---|---|
| 1 | 1800 | 130 | 86 |
| 2 | 600 | 80 | 11 |
| 3 | 750 | 90 | 15 |
| 4 | 1750 | 110 | 84 |
| 5 | 740 | 85 | 14 |

$$\begin{cases} \dfrac{dS}{dt} = m-(\beta I+m)S-p\sum_{n=0}^{\infty}S(nT^-)\delta(t-nT), \\ \dfrac{dI}{dt} = \beta IS-(m+g)I \end{cases} \quad (12)$$

$$t \neq nT, n=0,1,2,\cdots n$$

where $S(nT^-)=\lim_{\varepsilon\to 0} S(nT-\varepsilon), \varepsilon>0$. $T$ is the period of pulse vaccination and $\beta$ is the rate of susceptible becoming infectious. $g$ represents the recovery rate of infection. $m$ stands for the born rate, which is equal to death rate. $p$ is the rate of vaccination.

In the time interval $t_0=(n-1)T<t\leq nT$ an "infection-free" solution must satisfy:

$$S(t)=1-\frac{pe^{mT}}{e^{mT}-(1-p)}e^{-m(t-t_0)}-p(1-\frac{pe^{mT}}{e^{mT}-(1-p)}e^{-mT})\int_0^t\delta(t-nT), \quad (13)$$

$$\tilde{I}(t)=0,$$

From the above formula, we can get the following relations:

$$\frac{(mT-p)(e^{mT}-1)+mpT}{mT(p-1+e^{mT})}<\frac{m+g}{\beta}$$

Suppose that $s_0=s(t)$ is the number of susceptible $S$ after the (n-1) *Th* vaccination pulse at time $t_0=(n-1)T$, so we can get the following solution from formula (13):

$$S(t)=\begin{cases} 1-(1-S_0)e^{-m(t-t_0)}, t_0=(n-1)T\leq t<nT \\ (1-p)(1-(1-S_0)e^{-m(t-t_0)}), t=nT \end{cases} \quad (14)$$

In this article we use typical parameters that are representative of measles dynamics [21], as follows: $m$ = 0.02, $\beta$ = 1800, $g$ = 100. It is useful to note that for the standard measles parameters [22], $p$=0.95. So through the above formula we can get $T\leq 5.6$. In this condition, we set $T$=5. So the first dispensing point will be opened at $t$=0, and the second is $t$=5. According to the formula (14), as well as with the population, economic development, disaster degree of affected areas, the vaccine demand function is obtained. Then the demand of the affected area is counted. The demand function and demand of every affected area is displayed in Table 3. There will be many periods, we only consider the two periods in order to make the problem simple. We also suppose that the rescue effect should be more than 88%.So we can

If one area suffers from the measles, the population in that area will be composed of three groups of individuals: susceptible (S), infectious (I) and recovered (R), whose dynamics are modelled by the standard SIR equations. We suppose that the emergency rescue centres can provide the vaccination to the demand area in order to reduce the number of infection people. When pulse vaccination is incorporated into the SIR model [21], the system can be rewritten as follows:

transform the objective function (2) into the constraint condition which can be described as: $\sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{J}x_j a_{kij} / \sum_{i=1}^{I}\sum_{k=1}^{k}c_{ik} \geq 88\%$.

TABLE 3 Demand function and demand of every affected area

| Area j | Ci1(t) | Ci1 | Ci2(t) | Ci2 |
|---|---|---|---|---|
| 1 | 8.2(1-0.05exp(-0.02t)) | 39.032 | 8.2(1-0.9523exp(-0.02(t-5))) | 3.84 |
| 2 | 7.5(1-0.05exp(-0.02t)) | 35.7 | 7.5(1-0.9523exp(-0.02(t-5))) | 3.5122 |
| 3 | 9.3(1-0.05exp(-0.02t)) | 44.268 | 9.3(1-0.9523exp(-0.02(t-5))) | 4.3551 |
| 4 | 4.5(1-0.05exp(-0.02t)) | 21.42 | 4.5(1-0.9523exp(-0.02(t-5))) | 2.1073 |
| 5 | 0.24(1-0.05exp(-0.02t)) | 1.1424 | 0.24(1-0.9523exp(-0.02(t-5))) | 0.1123 |
| 6 | 1.5(1-0.05exp(-0.02t)) | 7.14 | 1.5(1-0.9523exp(-0.02(t-5))) | 0.7024 |
| 7 | 1.8(1-0.05exp(-0.02t)) | 8.568 | 1.8(1-0.9523exp(-0.02(t-5))) | 0.8429 |
| 8 | 0.78(1-0.05exp(-0.02t)) | 3.7128 | 0.78(1-0.9523exp(-0.02(t-5))) | 0.3653 |

Additionally, there are other conditions: $h$=6, $O$=5500, $C$=700, $q$=6.1. Once the dispensing point is set up in the early time, it will not be closed later. All of the decision cases can be described in Table 4. In connection with all the options, the total cost of the emergency rescue system can be stated in Table 5, and the rescue effect of the emergency rescue system is showed in Table 6.So the optimal solution is: the dispensing point 1 and 6 are built at $t$ = 0, the point 5 is set up at $t$ = 5. The total cost of the emergency rescue system is 5499.3, and the rescue effect of the emergency rescue system is 88.4%.

TABLE 4 All the decision case

| Possible point during the period of 1th | Possible point during the 2th period |
|---|---|
| (1,4) | (1,4,3) |
| | (1,4,5) |
| | (1,4,6) |
| (1,6) | (1,6,3) |
| | (1,6,4) |
| | (1,6,5) |
| (4,6) | (4,6,1) |
| | (4,6,3) |
| | (4,6,5) |

TABLE 5 Total transportation cost of all the decision case

| Possible point during the first period | Total cost during the first period | Possible point during the second period | Total cost during the second period | Total cost during the two periods |
|---|---|---|---|---|
| **(1,4)** | 4630.2 | (1,4,3) | 1037.5 | **5667.7** |
| | | (1,4,5) | 878.1 | **5508.3** |
| | | (1,4,6) | 1963.0 | **6593.2** |
| **(1,6)** | 4621.2 | (1,6,3) | 1037.5 | **5658.7** |
| | | (1,6,4) | 1951.4 | **6572.6** |
| | | (1,6,5) | 878.1 | **5499.3** |
| **(4,6)** | 4714.2 | (4,6,1) | 2033.0 | **6747.2** |
| | | (4,6,3) | 1037.5 | **5751.7** |
| | | **(4,6,5)** | **878.1** | **5592.3** |

TABLE 6 Rescue effect of all the decision case

| Possible point during the first period | Rescue effect during the first period | Possible point during the second period | Rescue effect during the second period |
|---|---|---|---|
| **(1,4)** | 100% | (1,4,3) | **94.71%** |
| | | (1,4,5) | **88.4%** |
| | | (1,4,6) | **100%** |
| **(1,6)** | 98.77% | (1,6,3) | **94.71%** |
| | | (1,6,4) | **100%** |
| | | (1,6,5) | **88.4%** |
| **(4,6)** | 97.53% | (4,6,1) | **100%** |
| | | (4,6,3) | **94.71%** |
| | | **(4,6,5)** | **88.4%** |

## 5 Conclusions

The location of emergency facility is an important research domain in the field of disaster relief. In view of the characteristics of urgency, the location of emergency facilities plays an important role in rescue management, and it determines the efficiency and effectiveness of the emergency system. A reasonable emergency facility location decision can improve the efficiency and effectiveness of emergency management. In this paper, a multi-objective programming model that balances the total cost of emergency facility and the effect of rescue is proposed. The demand for the rescue materials is calculated by an indefinite integral, and the effect of rescue is measured by the ratio of the arrival quantity of the rescue material to the demand. The model is solved by the Greedy Dropping heuristic. Through numeric simulation, the model is proved to be effective, and the theoretical reference can be used by the decision makers for coping with the public health emergencies.

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