An Optimal Dynamic Network Planning Model for Eradication of Ebola

Abstract

Ebola virus spread widely and the situation become more and more serious, prevention and cure of this infectious disease is our critical and urgent task. In this paper, we have built a realistic, sensible, and useful model that considers not only the spread of the disease, the quantity of the medicine needed, possible feasible delivery systems, locations of delivery, speed of manufacturing of the vaccine or drug, but also any other critical factors to optimize the eradication of Ebola. Our model is an integrated one by combining the spread model of the Ebola disease and the location–allocation model of delivery systems.

In the spread model of the Ebola disease, based on traditional SIR, we give appropriate modification with nonlinear infection rate. In addition, we analyze the modification based on SIR with stochastic model. We can simulate percentage change of the susceptible people and patients before and after medication and predict the demand of drugs due to the increase of the number of people who suffering from Ebola in disease positions. Furthermore, the prediction for the demand of medicine is essential for following location–allocation schedule.

In the location–allocation model of delivery systems, we can determine the optimal position where delivery centers should be established with the demand of different extent based on the mixed programming algorithm. Once the disease incidence of an area increases suddenly, the delivery system will make an optimization strategy on how to allocate medicine for transportation with the location-allocation model depending on the demand at this moment. So we can decide how much medicine should be transported and transportation routine at minimum cost and minimum time. Thus, the situation of epidemic is under control and will obtain the aim of eradication of Ebola with the efficacy of medicine by using this dynamic integrated model.

We verify the feasibility of this model based on the historical data of Ebola disease in West Africa in 2014. We can find an optimal plan on how to locate the delivery center and how to allocate the drug. The programming process realizes the unity of the demand prediction of disease position and allocation of quantity of drug in transportation which can change allocation strategy dynamically. Thus, it can be of great value in terms of the eradication of Ebola.

Our model can adaptively be applied to predict the spread of various kind of virus with proper parameter fitting. It is a general framework for providing the best schedule of eradication of spread diseases and will be effective enough to control current spread situation. More algorithms can be developed and combined in our framework.
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1 Restatement of the Problem

Ebola is a rare virus of high mortality which outbroke in West Africa in 2014 [1-3]. The World Medical Association has announced that their new medication could stop Ebola and cure patients whose disease is not yet advanced. How to build a realistic, sensible, and useful model that considers not only the spread of the disease, the quantity of the medicine needed, possible feasible delivery systems, locations of delivery, speed of manufacturing of the vaccine or drug, but also any other critical factors is very important to optimize the eradication of Ebola, or at least its current strain.

The above problem can be regarded as a well-known facility location–allocation problem under customer demands. This problem has received much attention from other researchers and it has been analyzed in a number of different ways. However, none of these studies has considered to be applied to optimize the eradication of Ebola.

In this paper, we consider several plants, some potential delivery centers, and a set of customers. Besides, demand of customer is stochastic. The problem is described as follows.

(1) Establish an Ebola spread model considering the spread of the disease and illustrate the quantity of the medicine needed.

(2) Based on the customers demand, capacities of plants, and locations of plants, customers and potential delivery centers, how to locate delivery centers, how to allocate customers to delivery centers, and how much inventory should be held in each delivery center.

2 Assumptions

For the spread of the Ebola disease, we made the following assumptions:

(A1) Total population of a disease position is a constant before medication;

(A2) Patients will become permanently immune people after recovering from infectious diseases. Also, susceptible people become permanently immune people after vaccination;

For the location–allocation problem under customer demands, we make several assumptions to simplify the model so that the model can be established:

(B1) Only transport one kind of medicine;

(B2) The production capacity of each plant is equal and always can meet the needs of disease position;
(B3) Only consider the position of delivery center within a certain range of options (all disease positions);
(B4) Every disease position only supplied by single delivery center;
(B5) The cost of transporting certain quantity of drugs is proportional to its quantity.

3 The Optimal Network Planning Model to the Eradication of Ebola

3.1 The Spread Model of the Ebola Disease

3.1.1 Definitions

\[ S(t) \] — The percentage of susceptible account for total population;
\[ I(t) \] — The percentage of infective account for total population;
\[ R(t) \] — The percentage of removed account for total population;
\[ \partial \] — Recovery rate;
\[ \mu \] — Vaccination rate;
\[ \frac{kSI}{1+\partial t^2} \] — Infection rate of serious disease.
\[ \lambda_i \Delta t \] — The possibility of adding an infected person based on \( i \) infected people;
\[ \mu_i \Delta t \] — The possibility of curing an infected person based on \( i \) infected people;
\[ \alpha_i \Delta t \] — The possibility of a susceptible person can get vaccinated based on \( i \) infected people;

3.1.2 The spread model based on SIR with a nonlinear infection rate

The most fundamental part of the model is the simulation and the prediction to the spread of the Ebola disease, so we consider the spread model based on SIR [4, 5].

In the SIR spread model, we usually define the infection rate as \( \lambda \). This infection rate is a fixed coefficient based SIR model. But we found that the actual data did not fit this model exactly. Therefore, we generally think the infection rate is related to the number of the patient. According to the actual situation of the spread of infectious diseases, nonlinear infection rate seems reflect the spread characteristics of the infectious diseases better. A typical nonlinear infection rate
\[ g(I)S = \frac{kI^pS}{1 + \partial I^q} \]  

\[ (1) \]

has been applied to several infectious diseases models [4, 5]. Taking into account the psychological impact of susceptible people due to the inhibition to the disease, we adopt a non-monotonic infection rate

\[ g(I)S = \frac{kIS}{1 + \partial I^2} \]  

\[ (2) \]

to describe the psychological impact when the number of a kind of serious infectious diseases becomes larger [6].

Thus, we have a spread model as follows:

\[
\begin{align*}
&\frac{dS}{dt} = -\frac{kSI}{1 + \partial I^2} - \alpha S \\
&\frac{dl}{dt} = \frac{kSI}{1 + \partial I^2} - \mu I \\
&S(t) + I(t) + R(t) = 1
\end{align*}
\]

\[ (3) \]

3.1.3 The modification based on SIR with stochastic model

Based on stochastic model, we can improve the spread model in terms of the SIR model of fixed population [4].

This modified model adopt fixed infection rate for the simplification of the model. Consider the entire communication process, assuming that \( \Delta t \) is very small, the possibility of two events happening at the same time is extremely small. So we have

\[
\begin{align*}
&P[I(t + \Delta t) = i - 1, R(t + \Delta t) = r + 1, S(t + \Delta t) = s | I(t) = i, R(t) = r, S(t) = s] = \mu_i \Delta t + o(\Delta t) \\
&P[I(t + \Delta t) = i + 1, R(t + \Delta t) = r, S(t + \Delta t) = s - 1 | I(t) = i, R(t) = r, S(t) = s] = \lambda_i \Delta t + o(\Delta t) \\
&P[I(t + \Delta t) = i, R(t + \Delta t) = r + 1, S(t + \Delta t) = s - 1 | I(t) = i, R(t) = r, S(t) = s] = \alpha_i \Delta t + o(\Delta t) \\
&P[I(t + \Delta t) = i, R(t + \Delta t) = r, S(t + \Delta t) = s | I(t) = i, R(t) = r, S(t) = s] = 1 - \mu_i \Delta t - \lambda_i \Delta t - \alpha_i \Delta t + o(\Delta t) \\
&P[I(t + \Delta t) = a, R(t + \Delta t) = b, S(t + \Delta t) = c | I(t) = a, R(t) = b, S(t) = c] = \alpha(\Delta t), \\
&|i - a| \geq 2, |r - b| \geq 2, |s - c| \geq 2
\end{align*}
\]

The first equation to the fourth equation denoted as cured probability, probability of infection, vaccine probability, stability probabilistic, respectively. Thus, we have the differential equations regarding joint probability:

\[
\frac{dP_{ys}}{dt} = \mu_i P_{i+1,r-1,s} + \lambda_i P_{i,r,s+1} + \alpha_i P_{i-1,r+1,s} + (\mu_i + \lambda_i + \alpha_i) P_{i,r,s}
\]

Compared to the SIR model based on fixed population, the stochastic SIR model reflects
a cluster of possible curve referring random effect factors. But the total trend of these curves and the trend of SIR model based on fixed population is completely the same. When using the SIR model based on fixed population to predict, we can refer to their expectations or appropriate confidence intervals for corresponding prediction.

3.1.4 The Ebola spread model based on SIQR

Considering the actual situation, some patients are unable to spread the virus because of related isolation measures. We call these people isolated patients. So the model (4) can be modified as the SIQR model as follows:

\[
\begin{align*}
\frac{dS}{dt} &= A - \frac{kSI}{1+\delta I^2} - d_i S \\
\frac{dI}{dt} &= \frac{kSI}{1+\delta I^2} - (\gamma + \delta + d + p_1) I \\
\frac{dQ}{dt} &= \delta I - (\varepsilon + d + p_2) Q \\
\frac{dR}{dt} &= \gamma I + \varepsilon Q - dR
\end{align*}
\]  

(4)

where \( Q \) means the percentage of isolated patients account for total population. The equation \( S(t) + I(t) + Q(t) + R(t) = 1 \) still holds.

We can do the further analysis on the two kinds of stable points of the model \([4, 5]\). In terms of the improved SIQR model, we can judge the stability by threshold \( R_0 = \frac{A_i}{d_e m_0} \) according to the Liapunov function. When \( R_0 > 1 \), there are two balance points: disease-free equilibrium and the endemic equilibrium. In this case, if there are some patients at first, then there are still several patients eventually which form endemic. When \( R_0 < 1 \), it only exist disease-free equilibrium which means this kind of illness will become extinct finally.

3.2 The Location–Allocation Model of Delivery Systems

As shown in Fig. 1, we consider several plants, some potential delivery centers, a set of customers (disease positions) and one kind of medicine. There are three different types of delivery system because of the difference distribution of plants and disease position:

1) Plants—Delivery centers—Disease positions: The capacity of overall plants in a country can satisfied the demand of whole disease position in this country. So the routine of
delivering medicine is local plants to deliver centers then to disease positions.

2) Plants and international transit station (ITS)—Delivery center—Disease positions: The capacity of overall plants in a country cannot satisfy the demand of whole disease position in this country which should be assisted by ITS from other countries. So the routine of delivering medicine is local plants and ITS to deliver centers then to disease positions.

3) ITS—Delivery center—Disease positions: A country where disease position located does not have the required plants. That is to say, all medicines this country demand should completely assist ITS from other countries. So the routine of delivering medicine is ITS to deliver centers then to disease positions.

Considering actual conditions, we cannot establish a delivery center at every disease position which leads to the uneven distribution of resources. So we prefer to choose the position of delivery center from available disease positions. According to disease distribution map and plant status map, we find the distribution of plant and disease position is discrete. Most importantly, the fee of establishing delivery center and transporting drugs should be taken into consideration which restricts the allocation plan of delivering drugs from a plant to a disease position and affect the selection of delivery center [6-10]. Thus, we formulate a decentralized distribution center location model based on time-cost to determine the position of delivery center.

![Diagram](image)

**Fig. 1. The location–allocation scheme of delivery systems**

Delivery centers can be replenished by several plants together because of limited capabilities and capacities of plants. Demand of customers is stochastic. Customer is only supplied by single delivery center. The problem is described as follows. Given distribution of
demand customers, locations of plants and potential delivery centers, how to locate delivery centers, how to allocate customers to delivery centers, and how much inventory should be held in each delivery center. The objective is to minimize the expected total cost with the determination the position of delivery center. The total cost includes transportation cost (transportation cost from plants to delivery centers, transportation cost from plants to customers and transportation cost from delivery centers to customers), fixed cost of delivery centers, and inventory holding cost (inventory consists of working inventory and safety stock) of delivery centers and so on.

3.2.1 Definitions

\[ N \{ n_i | i = 1, 2, ..., N \} \] — A set of plants;

\[ M \{ m_j | j = 1, 2, ..., M \} \] — A set of alternative delivery centers;

\[ Q \{ Q_k | k = 1, 2, ..., Q \} \] — A set of disease positions;

\( C_i \) — The transportation cost from plant \( i \) to delivery center \( j \);

\( C_{jk} \) — The transportation cost from delivery center \( j \) to disease position \( k \);

\( f_j \) — The construction cost of delivery center \( j \);

\( t_{ij} \) — The transport time from plant \( i \) to delivery center \( j \);

\( t_{jk} \) — The transport time from delivery center \( j \) to disease position \( k \);

\( T_k \) — The maximum allowable transport time to disease position \( k \);

\( c_i \) — The quantity of drugs that plant \( i \) can supply;

\( b_j \) — The quantity of drugs that delivery center \( j \) can hold;

\( u_j \) — The inventory holding cost of delivery center \( j \);

\( a_k \) — The quantity of drugs that disease position \( k \) needs;

\( p \) — The maximum number of delivery centers needed;

\( Y_j \) — The possibility of alternative delivery center \( j \) has been chosen;

\( W_{ij} \) — The quantity of drugs transported from plant \( i \) to delivery center \( j \);

\( W_{jk} \) — The quantity of drugs transported from delivery center \( j \) to disease position \( k \).
3.2.2 The location–allocation model based on time-cost

(1) Decision variables

We use $Y_j$ to define the possibility of alternative delivery center $j$ has been chosen which $Y_j = 1$ means alternative delivery center $j$ has been chosen as a delivery center and $Y_j = 0$ means alternative delivery center $j$ has not been chosen as a delivery center.

(2) Demand quantity

The demand of a disease position is an available variable which is calculated by the number of patients. Its value can approximately be a constant in a certain phase. But as phase changes, the number of patients in a disease position changes apparently. We consider the demand of drugs due to the changing number of patients.

(3) Total cost

Our aim is to propose a feasible plan to delivery drugs while optimize the total expense in actual transportation. Total expense includes construction cost, transportation cost and management fees.

The transportation cost includes two parts. One is the freight from plant $i$ to delivery center $j$, and the other is the freight from delivery center $j$ to disease position $k$. Especially, the transportation cost is proportional to the distance between two places. We use $\sum_{i\in N} \sum_{j\in M} C_{ij}W_{ij} + \sum_{j\in M} \sum_{k\in K} C_{jk}W_{jk}$ to express it.

The fixed cost of delivery centers includes construction investment, equipment purchase expenses, maintenance of equipment and machinery and so on. While delivery center is established, the construction cost of it is a constant which cannot be neglected. We use $\sum_{j\in M} f_jY_j$ to express it.

The inventory holding cost refers to the management cost during the storage in delivery center. Inventory consists of working inventory and safety stock. We use $\sum_{i\in N} \sum_{j\in M} u_jW_{ij}$ to express this.

So, we have the following objective function:

$$\text{Min } Z = \sum_{i\in N} \sum_{j\in M} C_{ij}W_{ij} + \sum_{j\in M} \sum_{k\in K} C_{jk}W_{jk} + \sum_{j\in M} f_jY_j + \sum_{i\in N} \sum_{j\in M} u_jW_{ij}$$
(4) Constraint conditions

1) Supply constraint: Quantity of drugs transported from plant $i$ cannot exceed its supply,
$$\sum_{j \in M} W_{ij} \leq c_i, i \in N.$$  

2) Demand constraint: Quantity of drugs transported to disease position $k$ should satisfy the need of disease position $k$,
$$\sum_{j \in M} W_{jk} \geq a_k, k \in K.$$  

3) Capacity constraint: The purchase quantity of the alternative delivery center $j$ is less than the capacity of the alternative delivery center $j$,
$$\sum_{i \in N} W_{ij} \leq b_j Y_j, j \in M.$$  

4) Balance constraint:
$$\sum_{i \in N} W_{ij} = \sum_{k \in K} W_{jk}, j \in M.$$  

5) Time constraint: The sum of transport time from plant $i$ to alternative delivery center $j$ and transport time from delivery center $j$ to disease position $k$ should be less than the maximum allowable transport time to disease position $k$. Access to relevant news report, the incubation period of Ebola is 2 to 21 days which is difficult to discover because of the imperceptible symptoms. In medium period, symptoms become obvious and the demand for drugs increases heavily. Since the time from medium period to advanced medium period only takes 7 to 14 days. So the maximum allowable transport time to disease position $k$ between 7 to 14 days.
$$(t_i + t_{jk}) Y_j \leq T_k, k \in K,$$

6) Quantity constraint:
$$\sum_{j \in M} Y_j \leq p,$$

7) Non-negative constraint:
$$Y_j = 0,1 \quad j \in M,$$
$$W_{ij} \geq 0, W_{jk} \geq 0, \quad i \in N, j \in M, k \in K.$$  

Considering all of the above aspects, we obtain the following optimal model.

**The object function:**
Min \[ Z = \sum_{i \in N} \sum_{j \in M} C_{ij} W_{ij} + \sum_{j \in M} \sum_{k \in K} C_{jk} W_{jk} + \sum_{j \in M} f_j Y_j + \sum_{i \in N} \sum_{j \in M} u_j W_{ij} \] (5)

Subject to:
1) \[ \sum_{j \in M} W_{ij} \leq c_i, i \in N \]
2) \[ \sum_{j \in M} W_{jk} \geq a_k, k \in K \]
3) \[ \sum_{i \in N} W_{ij} \leq b_j Y_j, j \in M \]
4) \[ \sum_{i \in N} W_{ij} = \sum_{k \in K} W_{jk}, j \in M \]
5) \[ (t_{ij} + t_{jk}) Y_j \leq T_k, k \in K \]
6) \[ \sum_{j \in M} Y_j \leq p \]
7) \[ Y_j = 0, 1, j \in M \]
8) \[ W_{ij} \geq 0, W_{jk} \geq 0, i \in N, j \in M, k \in K \]

We give our algorithm in **Algorithm 1** to solve the model:

<table>
<thead>
<tr>
<th>Algorithm 1. The Specific Process of Integrated Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1</strong> Consider ( C_m^p (p \leq m) ) permutations of ( Y_j ), turning 0-1 programming into linear programming;</td>
</tr>
<tr>
<td><strong>Step 2</strong> Filter feasible solution under filter conditions concerning ( p ) and ( T_k );</td>
</tr>
<tr>
<td><strong>Step 3</strong> Determine the coefficients of matrix;</td>
</tr>
<tr>
<td><strong>Step 4</strong> Call linear programming toolbox.</td>
</tr>
</tbody>
</table>

### 3.2.3 The modification of location–allocation model

In this problem, we consider customer can be either served by delivery centers or replenished by plant directly. The objective is to minimize the expected total cost with the satisfaction of desired cycle service level. The satisfaction of desired cycle service level is motivated by the fact that the company wants to make sure that the strategic customers (with big demand) have short lead time and other customers can have relatively long lead time. The total cost particularly includes penalty cost (influence that the strategic customers are not satisfied) in addition to above costs.

The strategic customer is described as some disease positions where the number of total
infections or newly infections in some disease positions is particularly larger compared with other disease positions. The strategic customers are shown in Fig. 2, where the color is much darker than surrounding areas. For example, total amount of the confirmed cases of PORT LOKO is twice of KAILAHUN according to the data in January 28, 2015. So it is essential to consider the severely infected area as a delivery center. That is to say, cycle service level of this area increases. When severe infection area is not chosen as a delivery center, the delay of treatment will result in greater losses due to the death of infected staff. So we propose the notion of punishment factor $\alpha$ to explain this loss. Assumed that position $s$ where strategic customers located should be delivered directly by plants and transportation time should be less than $T_{km}$ which will have extra punitive damage cost when exceeds this range.

Thus, we infer a penalty function $\alpha^*(\sum_{i\in N} T_{is} + \sum_{k\in K} T_{sk} - \sum_{k\in K} T_{km})$ to describe the damage cost because of the delay of transportation.

The modified model is shown as follows:

**The object function:**

$$\text{Min} \quad Z = \sum_{i\in N} \sum_{j\in M} C_{ij} W_{ij} + \sum_{j\in M} \sum_{k\in K} C_{jk} W_{jk} + \sum_{j\in M} f_{j} Y_{j} + \sum_{i\in N} \sum_{j\in M} u_{ij} W_{ij} + \alpha^* (\sum_{i\in N} T_{is} + \sum_{k\in K} T_{sk} - \sum_{k\in K} T_{km}) \quad (6)$$
3.3 The Integration of the Spread Model and the Location–Allocation Model

In the previous model, we established the spread model based on SIR and the location-allocation model based on time-cost and service level. We also verify the effectiveness and feasibility of these models through examples. Now, we will take two factors above into consideration and propose an integrated model in order to achieve the purpose of the complete eradication of Ebola. This model discusses the infection, prediction, location and allocation together.

3.3.1 Definitions

\(S_k(t)\) — The percentage of susceptible people account for total population in disease position \(k\);

\(I_k(t)\) — The percentage of patients who suffering from Ebola account for total population in disease position \(k\);

\(R_k(t)\) — The percentage of immune people account for total population in disease position \(k\);

\(N_k\) — The population of disease position \(k\);
3.3.2 The integrated model

Time is the most important factor we should consider. The number of infections will show explosive growth if we do not offer effective medication in a timely manner which is the worst case that we do not want to see. Thus, it is critical to deliver medicine in time to control the spread of Ebola.

The medicine demand is the key to connect two models together, since we can calculate the value of it according the number of patients. Also, the demand constraint condition of the location-allocation model is related to it. Accurate prediction of the medicine demand can not only save costs, avoid waste, but also can make the structure of drug allocation more rational.

Based on the above analysis, we establish the integrated hybrid model as follows that combine the spread model with the location-allocation model because of the consistent demand for medicine.

\[
\begin{align*}
\text{Min} & \quad Z = \sum_{i \in N} \sum_{j \in M} C_{ij} W_{ij} + \sum_{j \in M} \sum_{k \in K} C_{jk} W_{jk} + \sum_{j \in M} f_j Y_j + \sum_{i \in N} \sum_{j \in M} u_j W \\
a_k &= I(t) \frac{\text{N}_k}{\text{D}} \\
\frac{dS_k}{dt} &= -\frac{kS_k I_k}{1 + \partial I_k^2} - \alpha S_k \\
\frac{dI_k}{dt} &= \frac{kS_k I_k}{1 + \partial I_k^2} - \mu I_k
\end{align*}
\]

Also, we have:

\[S_k(t) + I_k(t) + R_k(t) = 1\]

And the constraint conditions in Section 3.2 still satisfied in this model.

The dynamic characteristic of integrated model: We can adjust the allocation plan dynamically depend on the different demand of disease positions based on the integrated model. If allocation plan does not change with the variation of demand, irrational distribution of resources will make the epidemic out of control. Therefore, the dynamic characteristic has a special meaning to this model.

The definition of threshold: Threshold means the percentage of maximum allowable number of infections. This concept allows for the prediction and control of disease positions. After determining the threshold, we can calculate the number of patients correspondingly. Because of the proportional relationship between the number of patients and the demand for
drugs, we have the maximum demand for drugs. Thus, we can get the optimal solution within certain time. Once a region reaches the threshold of disease incidence, relevant agencies will quickly assign certain quantity of medicine to the area from near plants and control local epidemic situation.

The key steps lie in the specific process of this model.

<table>
<thead>
<tr>
<th>The Specific Process of Integrated Model</th>
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<tbody>
<tr>
<td><strong>Step 1</strong></td>
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<td><strong>Step 2</strong></td>
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<td><strong>Step 3</strong></td>
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<td><strong>Step 4</strong></td>
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<tr>
<td><strong>Step 5</strong></td>
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</table>

4 The Experimental Results

4.1 Simulation Studies of the Spread Model

Fitting (3) of the spread model to the data we collect from CDC of total cases among three countries, we get the curve in Fig. 3, Fig. 4 and Fig. 5 [7].

Fig. 3. Prediction of Guinea after and before medication.
After vaccination, susceptible people become permanently immune people. Patients become immune people after having drugs. So the trend of curve of \( I(t) \) and \( S(t) \) is both downward until the value limited to zero. After medication, each country obtains the aim to control the spread of Ebola and realize the eradication of Ebola. But the decrease speed is different among three countries since the initial total case of Ebola in these countries is different.

Considering confidence interval of the stochastic SIR model, the coefficient of infection rate is not a constant. We can predict the number of infective in this confidence interval as shown in Fig. 6. The above three curves from top to bottom is the upper bound, optimal
estimates within confidence intervals and lower bound of $S(t)$. And the following three curves from top to bottom is the upper bound, optimal estimates within confidence intervals and lower bound of $I(t)$.

![Figure 6](image)

**Fig. 6.** Confidence intervals of $S(t)$ and $I(t)$

In Section 3.1.2, we made a hypothesis that the total population is a constant. But actually, because of the invalidity of drug in terms of patients with advanced, the death toll always has some influence on the total population. The trend of the infective and susceptible is shown in Fig. 7. when the death toll could not be ignored.

![Figure 7](image)

**Fig. 7.** Effect of death case compared with

We can see clearly that the trend of percentage of infective which considered the effect of death is below the trend of percentage of infective without considering the effect of death.
4.2 Results of Location–Allocation Model

As described in our model (6), we plan to choose some delivery centers from lots of potential locations so as to meet customers’ demand and request for the product with some different forms.

(1) Plants

According to the distribution of plants in Fig. 8, we find primary cities where plants gathered together. Since the quantity of plants in a certain city is different from each other, we can infer that the supply of cities where located plants is different. That is to say, the quantity of supply is proportional to the number of plants in a certain city. According to the distribution map of plants in Fig. 8, we conclude six primary cities where plants gathered. The specific information of these cities is shown in Table 1.

Fig. 8. The distribution map of plants

<table>
<thead>
<tr>
<th>City</th>
<th>Capacity of supply</th>
</tr>
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<tbody>
<tr>
<td>Conakry</td>
<td>2</td>
</tr>
<tr>
<td>Freetown</td>
<td>3</td>
</tr>
<tr>
<td>Bo</td>
<td>1</td>
</tr>
<tr>
<td>Koindu</td>
<td>3</td>
</tr>
<tr>
<td>Monrovia</td>
<td>3</td>
</tr>
<tr>
<td>Kakata</td>
<td>1</td>
</tr>
</tbody>
</table>
(2) Disease Position

We define the position of a high morbidity city with total confirmed cases greater than 300 or new confirmed cases in the past 21 days greater than 10 as disease positions. Meanwhile we also consider those neighboring cities with high morbidity as one position/unit, which means the disease positions in Table 2 is a set of several high morbidity cities which are closely located. For example, disease position at Port Loko includes PORT LOKO, FREETOWN, WESTERN RURAL three cities. Taking into account the social factors such as traffic and location, we locate the disease position at Port Loko. By this data processing method, we have six primary disease positions. The information of these disease positions is listed in Table 2 (according to latest distribution map from WHO) [8]. The percentage means the total confirmed cases.

<table>
<thead>
<tr>
<th>Disease Position</th>
<th>Country</th>
<th>Total confirmed cases</th>
<th>New confirmed cases in the past 21 days</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Port Loko</td>
<td>Sierra Leone</td>
<td>4431</td>
<td>251</td>
<td>74.08%</td>
</tr>
<tr>
<td>Bombali</td>
<td>Sierra Leone</td>
<td>985</td>
<td>18</td>
<td>16.47%</td>
</tr>
<tr>
<td>Kailahun</td>
<td>Sierra Leone</td>
<td>565</td>
<td>0</td>
<td>9.45%</td>
</tr>
<tr>
<td>Conakry</td>
<td>Guinea</td>
<td>389</td>
<td>19</td>
<td>35.20%</td>
</tr>
<tr>
<td>Macenta</td>
<td>Guinea</td>
<td>716</td>
<td>1</td>
<td>64.80%</td>
</tr>
<tr>
<td>Montserrado</td>
<td>Liberia</td>
<td>1,785</td>
<td>14</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Since we should select a certain number of disease position as deliver center from the set of position where demand points located in order to minimum the total cost of logistics and distribution systems, we have $p \leq M$. Considering the overlapping of distribution map of plants and cumulative case map, we can locate main disease positions. In the current situation of Ebola, they have 6 disease positions or potential delivery centers locations: Port Loko, Bombali, Kailahun, Conakry, Macenta, and Montserrado.

(3) Transportation cost

We can obtain the transportation cost since it is proportional to the distance between place A to place B which we can calculate from the map. Transportation cost between plant to potential delivery center is shown in Table 3. The transportation cost between potential delivery center to disease position is shown in Table 4.
Table 3. The transportation cost between plants to potential delivery centers

<table>
<thead>
<tr>
<th></th>
<th>Port Loko</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conakry</td>
<td>189</td>
<td>292</td>
<td>593</td>
<td>0</td>
<td>723</td>
<td>741</td>
</tr>
<tr>
<td>Freetown</td>
<td>119</td>
<td>246</td>
<td>417</td>
<td>265</td>
<td>573</td>
<td>577</td>
</tr>
<tr>
<td>Bo</td>
<td>210</td>
<td>194</td>
<td>180</td>
<td>402</td>
<td>336</td>
<td>341</td>
</tr>
<tr>
<td>Koidu</td>
<td>437</td>
<td>403</td>
<td>36.4</td>
<td>704</td>
<td>120</td>
<td>440</td>
</tr>
<tr>
<td>Monrovia</td>
<td>488</td>
<td>471</td>
<td>331</td>
<td>681</td>
<td>433</td>
<td>65.8</td>
</tr>
<tr>
<td>Kakata</td>
<td>552</td>
<td>535</td>
<td>394</td>
<td>744</td>
<td>362</td>
<td>32.5</td>
</tr>
</tbody>
</table>

Table 4. The transportation cost between delivery centers to disease positions

<table>
<thead>
<tr>
<th></th>
<th>Port Loko</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
</tr>
</thead>
<tbody>
<tr>
<td>Port Loko</td>
<td>0</td>
<td>110</td>
<td>400</td>
<td>189</td>
<td>556</td>
<td>548</td>
</tr>
<tr>
<td>Bombali</td>
<td>110</td>
<td>0</td>
<td>366</td>
<td>290</td>
<td>522</td>
<td>532</td>
</tr>
<tr>
<td>Kailahun</td>
<td>400</td>
<td>366</td>
<td>0</td>
<td>593</td>
<td>156</td>
<td>392</td>
</tr>
<tr>
<td>Conakry</td>
<td>189</td>
<td>290</td>
<td>593</td>
<td>0</td>
<td>723</td>
<td>741</td>
</tr>
<tr>
<td>Macenta</td>
<td>556</td>
<td>522</td>
<td>156</td>
<td>723</td>
<td>0</td>
<td>395</td>
</tr>
<tr>
<td>Montserrado</td>
<td>548</td>
<td>532</td>
<td>392</td>
<td>741</td>
<td>395</td>
<td>0</td>
</tr>
</tbody>
</table>

(4) Transportation time

Corresponding transportation time from plants to potential delivery centers is shown in Table 5. The transportation time from potential delivery centers to disease positions is shown in Table 6.

Table 5. The transportation time from plant to potential delivery center

<table>
<thead>
<tr>
<th></th>
<th>Port Loko</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conakry</td>
<td>2.63</td>
<td>4.2</td>
<td>7.77</td>
<td>0</td>
<td>9.35</td>
<td>10.05</td>
</tr>
<tr>
<td>Freetown</td>
<td>1.62</td>
<td>3.43</td>
<td>5.72</td>
<td>4.25</td>
<td>8.4</td>
<td>7.87</td>
</tr>
<tr>
<td>Bo</td>
<td>2.73</td>
<td>2.83</td>
<td>2.67</td>
<td>5.28</td>
<td>5.37</td>
<td>4.82</td>
</tr>
<tr>
<td>Koidu</td>
<td>5.9</td>
<td>5.87</td>
<td>0.7</td>
<td>9.57</td>
<td>2.02</td>
<td>5.93</td>
</tr>
<tr>
<td>Monrovia</td>
<td>6.38</td>
<td>6.48</td>
<td>4.42</td>
<td>8.95</td>
<td>5.58</td>
<td>1.17</td>
</tr>
<tr>
<td>Kakata</td>
<td>7.2</td>
<td>7.28</td>
<td>5.22</td>
<td>9.75</td>
<td>4.63</td>
<td>0.63</td>
</tr>
</tbody>
</table>
Table 6. The transportation time from delivery center to disease position

<table>
<thead>
<tr>
<th></th>
<th>Port Loko</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
</tr>
</thead>
<tbody>
<tr>
<td>Port Loko</td>
<td>0</td>
<td>1.75</td>
<td>5.2</td>
<td>2.63</td>
<td>7.88</td>
<td>7.47</td>
</tr>
<tr>
<td>Bombali</td>
<td>1.77</td>
<td>0</td>
<td>5.15</td>
<td>4.17</td>
<td>7.83</td>
<td>7.55</td>
</tr>
<tr>
<td>Kailahun</td>
<td>5.2</td>
<td>5.15</td>
<td>0</td>
<td>7.77</td>
<td>2.68</td>
<td>5.48</td>
</tr>
<tr>
<td>Conakry</td>
<td>2.63</td>
<td>4.17</td>
<td>7.77</td>
<td>0</td>
<td>9.35</td>
<td>10.05</td>
</tr>
<tr>
<td>Macenta</td>
<td>7.88</td>
<td>7.83</td>
<td>2.68</td>
<td>9.35</td>
<td>0</td>
<td>5.23</td>
</tr>
<tr>
<td>Montserrado</td>
<td>7.47</td>
<td>7.55</td>
<td>5.48</td>
<td>10.05</td>
<td>5.23</td>
<td>0</td>
</tr>
</tbody>
</table>

(5) Results of the location–allocation model based on time-cost

By linear programming mixed with 0-1 programming, we have solved this problem in a flexible way. Table 7 and Table 8 show different plans of choosing delivery centers among disease positions.

Table 7. Plans of choosing delivery centers among disease positions

<table>
<thead>
<tr>
<th>No</th>
<th>City</th>
<th>Port Loko</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
<th>Total cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>7554700</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>5522000</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>5198900</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>5062700</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>4582600</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>4324700</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>4170000</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3508900</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3766800</td>
</tr>
</tbody>
</table>

Note: No 1 to No 20 means 20 kinds of location–allocation plans;

1- this city has been chosen as a delivery center;
0- this city has not been chosen as a delivery center.

From Table 7, we can find No. 8 is an optimal plan on how to locate the delivery center and how to allocate the drug. The total cost under optimal plan is $3.5089 \times 10^6$. Specific
allocation schedules of this allocation plan are shown as Table 8 and Table 9, which is based on the demand in January 28, 2015.

Table 8. Drug traffic from plant to potential delivery center

<table>
<thead>
<tr>
<th></th>
<th>Port Loko</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conakry</td>
<td>219.3</td>
<td>0</td>
<td>0</td>
<td>2875.7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Freetown</td>
<td>4640</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bo</td>
<td>868</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>679</td>
</tr>
<tr>
<td>Koidu</td>
<td>0</td>
<td>0</td>
<td>2750</td>
<td>0</td>
<td>1890</td>
<td>0</td>
</tr>
<tr>
<td>Monrovia</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4640</td>
</tr>
<tr>
<td>Kakata</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1547</td>
</tr>
</tbody>
</table>

Table 9. Drug traffic from delivery center to disease position

<table>
<thead>
<tr>
<th></th>
<th>Port Loko</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
</tr>
</thead>
<tbody>
<tr>
<td>Port Loko</td>
<td>5727.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bombali</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Kailahun</td>
<td>0</td>
<td>0</td>
<td>994</td>
<td>0</td>
<td>0</td>
<td>1756</td>
</tr>
<tr>
<td>Conakry</td>
<td>116.7</td>
<td>1732</td>
<td>0</td>
<td>1027</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Macenta</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1890</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Montserrado</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6866</td>
</tr>
</tbody>
</table>

(6) Results of the location–allocation model based on service level

We take a specific city Montserrado as example to explain how our model work. For some reason, the epidemic is very serious which means Montserrado must be chosen as a delivery center in term of time. But if we forcibly constrain the selection of some delivery centers, the optimal plan will change as shown in Table 10 and Table 11.

Before considering service level, total cost is 4044000 and total time is 7.78h. while considering service level, total cost is 5498500 and total time is 4.2h. We can find the total cost increases when one of the following two situations occurs: (1) desired cycle service level increases (2) desired strategic customer is not satisfied. The reason for the increase of the total cost when situation (1) happens is obvious. If the desired cycle service level increases, the inventory levels in delivery centers will inevitably increase, which leads to an increase in
inventory holding cost. The reason that the total cost increases when situation (2) happens can be explained as follows. If the desired strategic customer is not satisfied, many infective cannot get timely treatment which will due to the death rate increasing greatly and total cost increases correspondingly. Also, the decrease of time reflects that the substance of service level is saving time at the expense of cost.

Table 10. Drug traffic from plant to delivery center

<table>
<thead>
<tr>
<th>Port</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conakry</td>
<td>0</td>
<td>3095</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Freetown</td>
<td>0</td>
<td>4640</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bo</td>
<td>0</td>
<td>868</td>
<td>0</td>
<td>0</td>
<td>679</td>
</tr>
<tr>
<td>Koidu</td>
<td>0</td>
<td>0</td>
<td>4640</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Monrovia</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4640</td>
</tr>
<tr>
<td>Kakata</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1547</td>
</tr>
</tbody>
</table>

Table 11. Drug traffic from delivery center to disease position

<table>
<thead>
<tr>
<th>Port</th>
<th>Bombali</th>
<th>Kailahun</th>
<th>Conakry</th>
<th>Macenta</th>
<th>Montserrado</th>
</tr>
</thead>
<tbody>
<tr>
<td>Port Loko</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bombali</td>
<td>5844</td>
<td>1732</td>
<td>0</td>
<td>1027</td>
<td>0</td>
</tr>
<tr>
<td>Kailahun</td>
<td>0</td>
<td>0</td>
<td>994</td>
<td>0</td>
<td>1890</td>
</tr>
<tr>
<td>Conakry</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Macenta</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Montserrado</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6866</td>
</tr>
</tbody>
</table>

4.3 Results of Integrated Model

First we verify the feasibility of integrated model considering the spread of the disease and delivery system at certain moment. We take Montserrado, Macenta, and Bombalid cities for example to examine the integrated model. The result is shown in Fig. 9. In order to evaluate the effectiveness of our model, we compare this simulation result with the number
trend of patients without medication in Fig. 10, and number trend of patients with common treatment in Fig. 11.

Compare Fig. 9 with Fig. 10, we find the number of infective decrease substantially. Thus, we verify the correctness of the spread model. Compare Fig. 10 with Fig. 11, the allocation model can realize the prediction of Ebola and deliver medicine early. Thus, the eradication of Ebola can be done in a faster way. Here reflects the advantages of the time-based allocation model compared to common case. Compare Fig. 9 with Fig. 11, we can clearly see that the number of infective has been effectively controlled under integrated model based on diseases prediction and medicine allocation. Compared with the previous two individual models, the integrated model achieves an optimal purpose while considering least time and least economic costs. Besides, we can see the spread of Ebola is under control after transportation. The number of patients is decreasing over time and Ebola is eradicated finally. The rationality and validity have been reflected by above three figures.

![Fig. 9. The number trend of patients without medication](image1)

![Fig.10. The number trend of patients with common treatment](image2)
Since the data of allocation plans under different demand is very large which cannot be shown in the paper, so we only use the different total cost under different demand to reflect the dynamic characteristic of integrated model.

The computational experiments described in this section are designed to evaluate the performance of our proposed method with respect to a series of test problems. In Fig.12, the demand and supply of each region are randomly distributed.

In order to show the effectiveness of our proposed model and method, we compare our solution with the solution obtained by simple and normal two-stage procedure (at the first stage, the location–allocation solutions are solved while ignore warehouse inventory holding cost, at second stage, the warehouse inventory holding cost is computed based on known warehouse location and customer allocation).
5 Robustness and Sensitivity Analysis

In order to further examine and validate the robustness and sensitivity of our methods, we discuss the situations under various conditions.

5.1 Analysis on the Parameters of the Ebola Spread Model

The infection rate, recovery rate and vaccination rate are primary coefficients in model (3). So we vary the value of them and examine the feasibility of these coefficients according to the simulation result as follows.

When we change the infection rate only, for example, increase the infection rate, we can see that the trend of the percentage of susceptible reduces faster and the trend of the percentage of infective increases faster which is shown in Fig.13.

When we change the recovery rate only, for example, increase the recovery rate, we can see that the trend of the percentage of susceptible decreases slower while the trend of the percentage of infective decreases faster which is shown in Fig.14.

When we change the vaccination rate only, for example, increase the vaccination rate, we can see that the trend of the percentage of susceptible decreases slower while the trend of the percentage of infective decreases faster which is shown in Fig.15.

![Fig.13. Trend of different infection rates](image.png)
5.2 Analysis on the Parameters in Location-Allocation Model

(1) The maximum allowable transport time to disease position \( k : T_k \)

The maximum allowable transport time to disease position \( k : T_k \), is as shown in Table 13.

<table>
<thead>
<tr>
<th>( T_k /h )</th>
<th>48</th>
<th>30</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Totalmoney</td>
<td>3058900</td>
<td>4040000</td>
<td>7070000</td>
</tr>
</tbody>
</table>
(2) The maximum number of delivery centers needed: $p$

Taking into account the practical factors, such as local transport conditions, geographical location, economic conditions (construction sites require costly distribution costs), some area cannot be chosen as a delivery center. The value of $p$ can affect the number of feasible solution after filtering in algorithm and related to the choose of the optimal solution. The relationship of $p$ and total cost is shown in Fig. 16.

![Fig. 16. The relationship of $p$ and total cost](image)

The above results demonstrate that our proposed method is a general framework for providing the best schedule of the eradication of Ebola. It can be allowed for the variation of conditions and be extended further in several ways for more realistic situations. Our method can make dynamic responses to the changing.

6 Strengths and Limitations

6.1 Strengths

1) In the spread model of the Ebola disease, we consider the actual situation of the spread of infectious diseases, and give a nonlinear infection rate to reflect the spread characteristics of the infectious diseases better.

2) The proposed location-allocation model for the delivery system can make an optimization strategy depending on the dynamic demand of the infectious diseases. Thus, the
situation of epidemic is under control and will obtain the aim of eradication of Ebola with the efficacy of medicine by using this dynamic integrated model.

3) Our model can adaptively be applied to predict the spread of various kind of virus with proper parameter fitting. It is a general framework for providing the best schedule of eradication of other disease and will be effective enough to control current spread situation. More algorithms can be developed and combined in our framework.

6.2 Limitations

There are a number of important areas which should be continued.

1) The proposed model needs to be verified by more practical cases to predict the spread of various kind of virus, and how to design the proper parameters for various kind of virus needs to be solved.

2) In our model, we only do simulations based on some assumptions. The insight into this field and the experience from the related experts are necessary.

3) The variation of conditions for the spread model of the Ebola disease should be taken into account further for more realistic situations, as such, other stochastic models should be considered in the further studies.

7 Conclusions

In this paper, we have built a realistic, sensible, and useful model that considers not only the spread of the disease, the quantity of the medicine needed, possible feasible delivery systems, locations of delivery, speed of manufacturing of the vaccine or drug, but also any other critical factors to optimize the eradication of Ebola. Our model includes the spread model of the Ebola disease and the location–allocation model of delivery systems. The spread model of the Ebola disease is the modification with nonlinear infection rate based on SIR. We can predict the demand of drugs due to the increase of the number of people who suffering from Ebola in disease positions. The location-allocation model for the delivery system will make an optimization strategy depending on the demand at this moment. We can decide the location where delivery centers established and how to allocate drugs from different plants to different delivery centers and from different delivery centers to different disease positions. We verify the feasibility of this model based on the historical data of Ebola disease in West Africa
in 2014. We can find an optimal plan on how to locate the delivery center and how to allocate the drug. The programming process realizes the unity of the demand prediction of disease position and allocation of quantity of drug in transportation which can change allocation strategy dynamically. Thus, it can be of great value in terms of the eradication of Ebola.

Moreover, our model can adaptively be applied to predict the spread of various kind of virus with proper parameter fitting. It is a general framework for providing the best schedule of eradication of other disease and will be effective enough to control current spread situation.

References