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Research on Optimization Analysis and Scheme Design of Multi Stage Material Dynamic Allocation

Siyu Zhao [1, a], Fengjiao Peng [1], Jin Chen [2,b,*]

[1]School of Statistics and Applied Mathematics, Anhui University of Finance and Economics, Bengbu 233030, China

[2]School of Accountancy, Anhui University of Finance and Economics, Bengbu 233030, China

[a]2579356825@qq.com, [b]1730607338@qq.com

Abstract

In response to the dynamic and time-varying characteristics of emergency supplies demand in the context of sudden epidemic situations, and considering the particularity of epidemic transmission mechanisms, an improved SEIR model was designed. Through the SEIR model, the demand for emergency rescue supplies after a public health event outbreak was predicted, with minimizing the loss of medical supplies shortage at each demand point as the first optimization objective and minimizing exceeding budget costs as the second optimization objective, an optimization model was constructed. In order to ensure the accuracy of distribution, the model parameters are adjusted weekly according to real-time data, and the scientificity and rationality of the model are verified by the case of emergency material distribution of novel coronavirus pneumonia in Shanghai in 2022. The results indicate that the proposed model and algorithm can provide decision support for emergency medical material management.

Keywords

Public health events; SEIR infectious disease model; Multi stage emergency material allocation; Dynamic decision-making.

1. Introduction

Major public health emergencies have the characteristics of high harm and strong destructive power. The guarantee of emergency rescue supplies directly affects the situation of major public health emergencies. The demand for emergency rescue supplies often increases explosively with the number of infected individuals, and emergency rescue supplies have problems such as uncertain demand and supply lag. In particular, the rapid development of the COVID-19 in Shanghai at the beginning of 2022 has led to a surge in demand for emergency supplies. However, with the passage of time and the continuous intervention of emergency supplies, the epidemic situation has gradually improved. Therefore, how to improve the accuracy of emergency supplies distribution in different stages of the epidemic and optimize the decision-making process is a key issue in the research of emergency supplies distribution.

Many scholars at home and abroad have conducted research on the allocation of emergency supplies. Xin Liu [1] proposed a method for predicting and allocating emergency drug demand in the event of sudden public health emergencies, taking into account the spread characteristics of the epidemic in various epidemic areas and the psychological pain costs of patients. Xue Jiang [2] established an emergency material allocation model with the goal of minimizing the expected shortage, and provided the optimal allocation plan for emergency materials in different situations, proving the effectiveness of centralized reserve and unified distribution strategies. Jin He [3] addresses the impact of uncertainty factors on emergency material allocation and establishes a method for emergency material allocation under uncertain conditions. Dong Bai [4] took the outbreak of COVID-19 in Hubei Province as an example, used the NSGA-Ⅱ algorithm to solve the problem, analyzed each distribution scheme from the perspective of the decision-maker, and used the material reserve of the emergency distribution center as a variable for sensitivity analysis. Li Ying's team [5] proposed a basic model and an improved model for the design of emergency logistics networks for sudden epidemics based on service levels, with the optimization goal of maximizing emergency service levels. Economou and Fakinos [6] constructed a continuous time Markov process to dynamically optimize emergency resource allocation under disaster changes. Büyüktahtakn et al. [7] focused on the Ebola epidemic in West Africa and constructed a mixed integer programming model considering the dynamic spatial distribution characteristics of the epidemic transmission, which was used to determine the location allocation of emergency resources.

In current research on the allocation of emergency supplies in major public health emergencies, the demand for emergency supplies usually comes from feedback from demand points on the demand for supplies or subjective judgments by relevant management departments. However, this method is prone to differences from actual demand and there is information lag in reality, making it difficult to respond in a short period of time; On the other hand, existing research on demand forecasting often fails to consider adjusting prediction model parameters, and in reality, with the changes in prevention and control measures and the improvement of medical level, parameters related to epidemic forecasting will also change. After the outbreak of major public health incidents, due to the fact that the workload of supply points during normal operations is far less than that of public health incidents, there will inevitably be a shortage of personnel in material management and logistics, as well as a shortage of logistics operation equipment, in the face of a large influx of materials. In view of this, based on existing relevant research, this article conducts in-depth research on the allocation of emergency rescue supplies in the event of major public health emergencies, such as uncertain demand, variable epidemic forms, and limited distribution capabilities. In demand forecasting, an improved SEIR infectious disease model is used to predict the trend of the epidemic and calculate the demand for emergency rescue supplies at each demand point in each cycle; In order to analyze the impact of prediction model parameters on the prediction results, this article compares the epidemic trends and material demand prediction results at different stages, and constructs a parameter adjustment model. In terms of material allocation, considering the people-oriented nature of emergency rescue, this article optimizes and models with the goal of minimizing the loss of medical supplies out of stock and exceeding budget costs at each demand point, and also takes into account the constraints of allocation capacity.

2. Problem Description and Modeling

After the outbreak of a major public health event, it is necessary to timely distribute rescue supplies to curb the rapid spread of the epidemic. However, there are many unresolved issues in the distribution process. In terms of allocation quantity, the decision to allocate emergency rescue supplies to various demand points often relies on feedback from demand points or subjective judgments from relevant management departments, leading to problems such as information lag and inaccurate allocation. In the implementation of emergency rescue supplies, due to the suddenness of public health incidents, the allocation process faces constraints such as insufficient rescue resources, insufficient manpower in material management and logistics, and insufficient logistics operation equipment. With the continuous changes in the development trend of the epidemic, the demand, allocation capacity, and quantity of emergency rescue materials have also changed. Therefore, constantly adjusting decisions based on real-time conditions is also an issue that cannot be ignored. In order to solve the above problems and improve the accuracy and efficiency of emergency material allocation in major public health emergencies, the maximum satisfaction rate and fastest allocation speed of rescue materials should be achieved under the constraints of limited rescue resources and allocation capabilities. At the same time, it is necessary to predict the demand for emergency rescue materials at the demand point and adjust decisions based on real-time conditions to avoid the problem of information lag. This paper takes the emergency supplies needed by novel coronavirus pneumonia in Shanghai in 2022 as an example, uses the modified SEIR infectious disease transmission model to describe the spread and spread of the epidemic situation, predicts the demand for emergency supplies through the change trend of the number of infected people, and constructs a multi-stage dynamic allocation optimization model of emergency medical supplies based on this demand, in order to provide decision-making support for emergency supplies deployment in the case of sudden outbreaks.

2.1. Improved SEIR model

The traditional SEIR model divides the research object into four categories: Susceptible (S), Exposed (E), Infected (I), and Recovered (R). The characteristics of each population are as follows:

(1) S(Susceptible) refers to healthy individuals who lack immune capacity and are susceptible to infection after contact with infected individuals;

(2) E (Exposed) refers to a person who has come into contact with an infected person but is not contagious, and can be used for infectious diseases with a latent period;

(3) I (Infectious) refers to an infectious patient who can transmit to S, transforming it into E or I;

(4) R (Recovered) refers to a person who has recovered from a disease and has immunity. If it is a lifelong infectious disease, it cannot be reclassified as S, E, or I. If the immune period is limited, it can be reclassified as S and subsequently infected.

This paper attempts to use the SEIR model as the basic model to study the spread and diffusion of novel coronavirus. In view of the announcement by the National Health Commission on January 26, 2020 that COVID-19 incubation period is infectious and the epidemic may lead to death of patients, this paper makes the following assumptions on the basis of the traditional SEIR model.

Assumption 1: Both infected and latent individuals have the ability to spread the virus, but the transmission rate is different;

Assumption 2: The infected person will no longer be infected after recovery;

Assumption 3: Without considering natural birth rates, mortality rates, and population mobility within each infected area;

Assumption 4: The epidemic will lead to patient death;

Assumption 5: Once infected, susceptible individuals can become latent individuals and become contagious, entering the incubation period.

The transformation process of the four populations is: Infected person I and latent person E respectively come into contact with susceptible person S, in order to increase the transmission rate β, $\beta 2$ will transform susceptible individuals into latent individuals E. The latent population will have a conversion rate α transformed into infected individuals, with some infected individuals dying at a mortality rate of d and others at a recovery rate of γ rehabilitation and no longer being infected.

Model parameters: T is the set of epidemic stages, t=1, 2, ..., T; N is the total number of people in the region; β is the probability of transmission from infected individuals to susceptible populations; β_2 is the probability of transmission from latent individuals to susceptible populations; α is the probability of latent individuals transforming into infected individuals; d

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is the probability of infected individuals dying due to illness; γ is the probability of infected individuals recovering from treatment to recovery.

State variables: S(t) is the number of susceptible individuals in time t, E(t) is the number of latent individuals in time t, I(t) is the number of infected individuals in time t, and R(t) is the number of recovered individuals in time t.

The epidemic diffusion process of demand points can be characterized by the following difference equation system:

$$S(t) = S(t-1) - \beta I(t-1)S(t-1)/N - \beta_2 E(t-1)S(t-1)/N \quad (1)$$

$$E(t) = E(t-1) + \beta I(t-1)S(t-1)/N + \beta_2 E(t-1)S(t-1)/N - \alpha E(t-1) \quad (2)$$

$$I(t) = I(t-1) + \alpha E(t-1) - \gamma I(t-1) - dI(t-1) \quad (3)$$

$$R(t) = R(t-1) + \gamma I(t-1) \quad (4)$$

$$N = S(t) + E(t) + I(t) + R(t) \quad (5)$$

Formula (1): the number of susceptible individuals at time t is equal to the number of susceptible individuals at time t-1, remove the number of susceptible individuals infected by infected individuals at time t-1, the infection rate is β; remove the number of susceptible individuals infected by latent individuals at time t-1, and the infection rate is β_2.

Formula (2): the number of lurkers at time t is equal to the number of lurkers at time t-1, plus the number of susceptible individuals who have been infected and become latent individuals at time t-1 ,the probability of infection is β; plus the number of susceptible individuals who have been infected by latent individuals at time t-1, the probability of infection is β_2; remove the number of latent individuals who have transformed into infected individuals at time t-1, with a conversion rate of α.

Formula (3): the number of infected individuals at time t is equal to the number of infected individuals at time t-1 plus the number of latent individuals at time t-1 who have transformed into infected individuals, and the conversion probability is α; remove the number of infected individuals who have recovered from infection at time t-1, and the probability of recovery is γ; remove the number of infected individuals who died due to illness at time t-1, the mortality rate is d.

Formula (4): the number of recovered patients at time t is equal to the number of recovered patients at time t-1, plus the number of recovered, who recovered form infected patients at time t-1 with the recovered probability of γ.

Formula (5): the total number of people in the infected area N is the sum of the number of susceptible, latent, infected, and recovered populations at time t.

Model parameter determination: The initial parameters in the SEIR infectious disease model can be calculated based on past epidemic related information or directly specified. Among them, the infection rate α can be set as the reciprocal of the incubation period of the epidemic; Recovery rate γ and the mortality rate d can be calculated by collecting the number of infected individuals, number of recovered individuals, and number of deaths in each cycle since the outbreak of the epidemic in the affected area by curve fitting, the calculation formula is$k = \frac{\overline{xy} - \bar{x} \cdot \bar{y}}{\overline{x^2} - (\bar{x})^2}$.When calculating the rehabilitation rate γ, When x is the number of infected individuals and y is the number of recovered individuals. When calculating the mortality rate d, x represents the number of infected individuals and y represents the number of deaths due to illness; The transmission rate of infected individuals β and the transmission rate of lurkers β_2 can be set according to the epidemic control situation; N is the total number of susceptible, latent, infected, and recovered populations at time t.

2.2. A multi-stage dynamic allocation model for emergency supplies

The distribution of emergency medical supplies considered in this article involves the distribution of supplies from multiple distribution centers to multiple demand points. It is assumed that the supply of supplies in each distribution center is constant at each stage and that infected and non infected individuals require different unit supplies. In addition, considering the impact of the spread of the epidemic, the decision-making cycle is divided into several stages, each stage requiring decision-making on the supply of materials from the distribution center to each demand point. Most of the traditional material distribution models aim to minimize the cost on the premise of meeting the demand for materials. However, in the context of emergency relief, the decision-makers first consider the demand satisfaction of each infected area. In special cases, they may even carry out relief at no cost, such as COVID-19, but for general emergency response, the decision-making department hopes that the cost of emergency rescue can be controlled within an effective range. On the other hand, due to the transportation of materials, this article will minimize the loss of medical supplies out of stock at each demand point as the first optimization objective, and minimize the cost exceeding the budget as the second optimization objective for modeling.

Model parameter: J is the set of demand points, I is the set of distribution centers, F is the cost budget, a is the quantity of medical supplies required by infected individuals, b is the quantity of medical supplies required by non infected individuals, c_{ij} is the unit transportation cost from distribution center i to demand point j, r_j is the storage cost of medical supplies per unit at demand point j, and G_i is the quantity of medical supplies at distribution center i.

Variables: y(t) represents the quantity of medical supplies consumed in the stage infected area, p(t) represents the existing quantity of medical supplies at stage t demand point, and $D_j(t)$ represents the demand at stage t demand point j.

Decision variables: x_{ij} is the quantity of medical supplies allocated from supply point i to demand point j in stage t, and *A(t)* is the total cost of medical supplies allocated in stage t.

Based on the above symbols, a multi-stage dynamic allocation optimization model for emergency medical supplies is proposed as follows:

$$\min Z = r_1 \sum_{j\in J} \sum_{t\in T} \frac{D_j(t) - \sum_{i=1}^{I} x_{ij}(t)}{D_j(t)} + r_2 \max\{0, \sum_{t=1}^{T} A(t) - F\} \quad (1)$$

$$\text{s.t.} \quad D_j(t) = I(t)a + [S(t) + E(t)]b \quad (2)$$

$$A(t) = \sum_{j=1}^{J} \sum_{i=1}^{I} c_{ij} x_{ij}(t) + \sum_{j=1}^{J} r_j \max\{0, p(t) - D_j(t)\}, \forall t \in T \quad (3)$$

$$p(t+1) = p(t) + \sum_{i=1}^{I} x_{ij}(t+1) - y(t), \forall t \in T, j \in J \quad (4)$$

$$y(t) = min\{D_j(t), p(t)\} \quad (5)$$

$$\sum_{j=1}^{J} x_{ij}(t) \le G_i \quad (6)$$

$$x_{ij}(t) \ge 0, \forall t \in T, j \in J, i \in I \quad (7)$$

The objective function (1) of the above model represents the weighted sum of minimizing the loss of medical supplies shortage at each demand point and minimizing the cost exceeding the budget. Constraint (2) represents the demand for emergency supplies at stage t demand point; Constraint (3) represents that the total cost of stage t is the sum of distribution cost and warehousing cost; Constraint (4) indicates that the current demand point j has an existing quantity of medical supplies equal to the sum of the remaining medical supplies in the previous stage and the current transportation of medical supplies; Constraint (5) indicates that the medical supplies consumed in stage t are the smaller value of existing supplies and material demand; Constraint (6) indicates that the total amount of materials distributed by each distribution center in each stage shall not exceed the supply of materials in that distribution center; Constraint (7) indicates that during stage t, the allocation center i is the demand point j, and the quantity of medical supplies transported is non negative.

3. Model Solving

3.1. Algorithm design

Firstly, the improved SEIR infectious disease model is used to predict the trend of the epidemic, and the demand for emergency rescue materials in affected areas at different time periods is predicted based on the changes in the epidemic situation; Establish an emergency material allocation model and use genetic algorithms to calculate the optimization results of allocating emergency materials to various disaster stricken areas.

Step 1: Set the initial parameters of the model. The parameters mainly include regional population, initial population of each type, correlation coefficient of influenza transmission, available supply of emergency rescue materials in each cycle, available distribution of distribution center in each cycle, and correlation coefficient of distribution optimization.

Step 2: Predict the trend of the epidemic. Substitute the influenza infection correlation coefficient and data into the SEIR model to obtain the number of susceptible, latent, infected, and recovered individuals per day in each cycle.

Step 3: Predict the demand for emergency rescue supplies. Calculate the daily demand for emergency rescue supplies for infected and non infected individuals.

Step 4: Optimize the allocation of emergency rescue supplies. Based on the prediction results of emergency rescue material demand, the optimal solution of the allocation optimization model is solved through genetic algorithm, and the allocation result is calculated.

Step 5: Record and output the distribution results of emergency rescue supplies for each disaster stricken area in each cycle.

3.2. SEIR model parameter design

In order to further explore the development trend of the spread of the epidemic and the demand for emergency rescue supplies in disaster stricken areas, the initial parameters of the SEIR infectious disease model were set based on historical relevant data: the probability of infected individuals infecting susceptible populations β and the probability of latent individuals infecting susceptible populations β_2 can be calculated based on the obtained epidemic related data, $\beta = 0.27, \beta_2 \approx 0.23$. The probability of converting latecomers to infected persons a is set as the reciprocal of the epidemic incubation period. The average incubation period of novel coronavirus epidemic is 7 days, then$\alpha = 1/7 \approx 0.143$. The recovery rate γ and mortality rate d were calculated based on the number of infections, rehabilitation, and deaths from February 28 to March 31, 2022. After curve fitting, the recovery rate $\gamma = 0.275$ and mortality rate $d = 0.09$ were obtained.

4. Case Experiment

The case of novel coronavirus pneumonia in Shanghai in 2022 was used to verify the effectiveness of the research on optimization of emergency supplies distribution under major public health events. Selecting six districts in Shanghai, including Pudong New Area, Minhang District, Baoshan District, Songjiang District, Jiading District, and Yangpu District, as demand centers and two distribution centers, this study aims to predict and allocate the demand for emergency rescue supplies from February 28 to May 14, 2022, after the outbreak of the epidemic. Reference [8] assumes a decision cycle of 15 days and divides the epidemic into five stages (15 days as one stage). Due to the unavailability of certain disaster data or the inability to collect data in disaster situations, the relevant data is set in a combination of actual data and partial simulation data.

4.1. Demand forecasting

The prediction results of the improved SEIR model on the epidemic trend of novel coronavirus pneumonia in Wuhan are shown in Figure 1. In the first half of 2022, the novel coronavirus pneumonia epidemic in Shanghai began on February 28, spread slowly under the control of the epidemic, entered the stage of large-scale outbreak in mid April, and until the closure and control was lifted in May, the epidemic infection was further aggravated. In the forecast data, the epidemic situation of novel coronavirus pneumonia in Shanghai spread slowly in the early stage, and entered the outbreak stage after the closure and control were lifted, which is consistent with the actual historical trend.

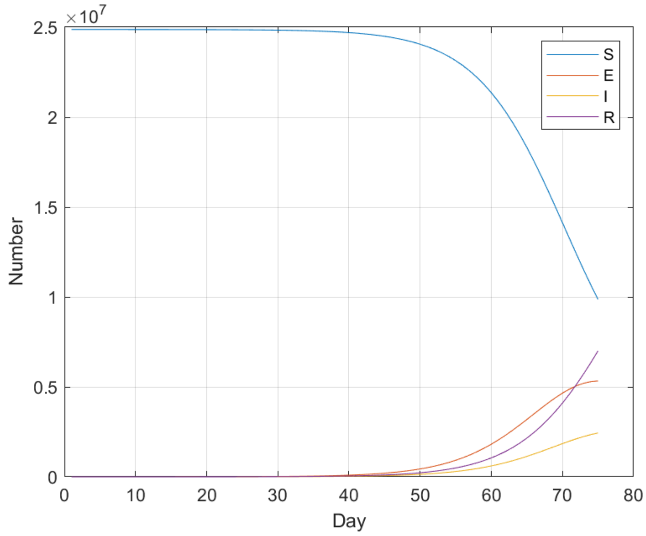

Figure 1. SEIR infectious disease model simulates the epidemic trend of novel coronavirus pneumonia in Shanghai

Substitute the parameters of the SEIR model into the emergency rescue demand prediction models of each demand center, and set the demand prediction function parameters a=1 and b=0.6. The use of infectious disease models to predict the demand for emergency rescue supplies in disaster stricken areas is shown in Table 1.

Table 1. Quantity of emergency supplies for each demand center

Date	Pudong New Area	Minhang	Baoshan	Songjiang	Jiading	Yangpu
Phase 1	5417	4361	3676	3683	4011	4901
Phase 2	6132	5499	4021	4765	4982	5327
Phase 3	7855	6480	5230	5669	5820	5841
Phase 4	8034	6570	5785	5982	6033	6090
Phase 5	8982	7211	5899	6480	6874	6206

4.2. Distribution of emergency supplies

The parameters of the emergency material allocation optimization model are assumed as follows due to the difficulty in finding real data: each patient needs 2 units of medical supplies per day, and the initial medical supplies for each city are 0.06 times the total population of the city. The unit transportation cost for supplies is 0.015 yuan per kilometer, and the storage cost for each item is 0.15 yuan per month. The total cost budget is 6 million yuan, and the supply of supplies in the distribution center is assumed to be [300, 450] million units, respectively.

Based on the predicted demand for emergency rescue supplies and other information in Table 2, the first goal is to minimize the loss of medical supplies out of stock at each demand point,

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and the second goal is to minimize the cost exceeding the budget. Emergency rescue supplies will be allocated from the supply point to the disaster stricken point. In this case, a genetic algorithm was used to implement the model through MATLAB 2021a, and the Pareto optimal solution was found, as shown in Figure 2. Due to the fact that minimizing the loss of out of stock at the affected point during the delivery process is the primary objective, and exceeding the budgeted cost is the secondary objective, the calculation results for the larger value of objective one and the smaller value of objective two are selected, as shown in Table 2.

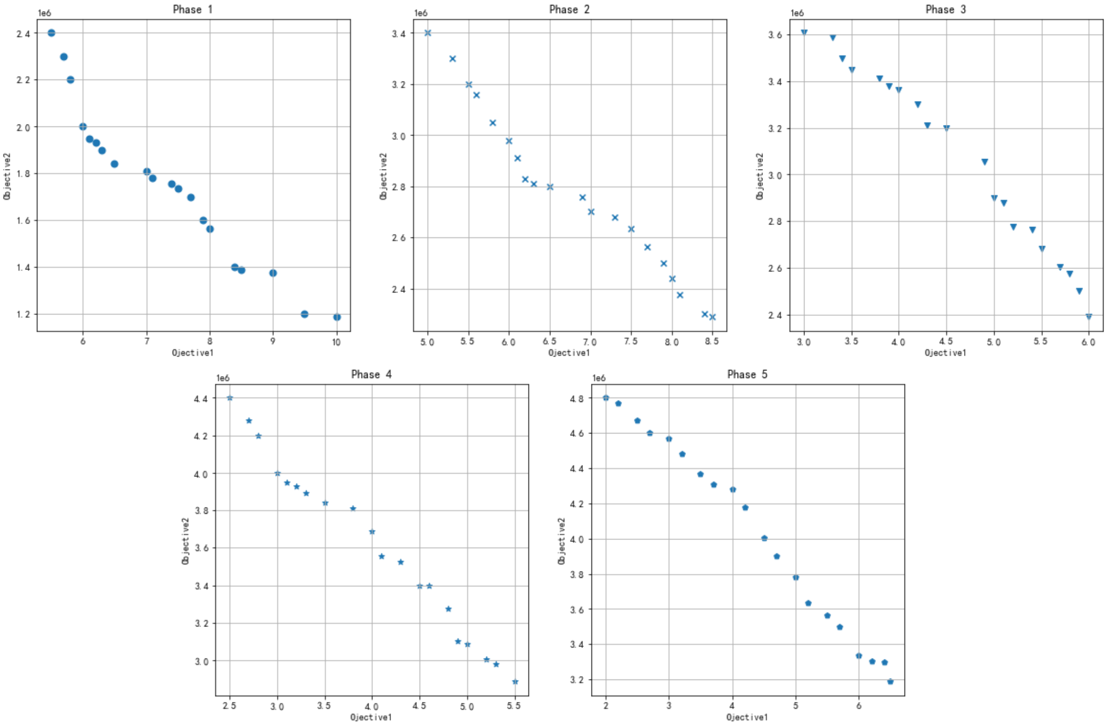

Figure 2. Pareto optimal solution for emergency material allocation

Table 2. Distribution Results of Emergency Supplies

Demand Center	Phase 1		Phase 2		Phase 3		Phase 4		Phase 5	
	supply center		supply center		supply center		supply center		supply center	
	1	2	1	2	1	2	1	2	1	2
Pudong New Area	2561	2474	2677	2580	3014	2932	3544	3269	3870	3463
Minhang	2310	2111	2501	2337	2889	2517	3174	2878	3543	3000
Baoshan	1856	1433	2001	1523	2431	1654	2681	1749	2703	1999
Songjiang	1863	1502	2088	1646	2500	1948	2788	2040	2811	2126
Jiading	2065	1731	2112	1807	2358	2019	2787	2135	2990	2544
Yangpu	2177	1960	2341	2132	2679	2442	2878	2550	3012	3176

From the allocation results, it can be seen that improving the SEIR model to predict the demand for emergency rescue supplies after a major public health event outbreak can provide a basis for solving the distribution problem of emergency rescue supplies. It can effectively solve the distribution problem of the rapid increase in the number of infected people and the demand for emergency rescue supplies after the outbreak of the epidemic, and provide timely allocation decision-making basis for the distribution center during the rescue process. In the material allocation model, when the supply of materials is limited and less than the demand, each disaster stricken point can obtain a certain amount of required emergency materials at each stage, ensuring that the losses caused by the unmet demand for emergency rescue materials are minimized while also ensuring the fairness of material allocation. It can be seen that the emergency rescue material demand prediction model and dynamic allocation model proposed by this research institute can quickly predict the demand for rescue materials in disaster stricken areas at various time points, improving the accuracy and effectiveness of rescue.

5. Summary

This article simultaneously considers the dynamic changes in the demand for emergency medical supplies caused by the spread of the epidemic, as well as the impact of emergency medical supplies distribution on the spread of the epidemic. An improved SEIR model is used to calculate various state variables in the system, which introduces the assumption of specific epidemic transmission mechanisms. Based on this, a multi-stage emergency medical supplies dynamic allocation optimization model is established, which balances the goals of minimizing medical supplies shortage losses at each demand point and minimizing exceeding budget costs in different epidemic stages. Unlike the traditional distribution model that only considers the current epidemic stage, this article optimizes the distribution of materials at each stage from a global perspective. The distribution center actively distributes materials for demand points, which has certain application contributions.

This article only considers the optimization problem with the goal of minimizing out of stock losses at demand points and minimizing budget costs, without considering the minimum allocation total path. In addition, this article only considers a single type of medical supplies, and only considers transportation and warehousing costs in the allocation cost. Therefore, in the case test, the allocation tasks of supplies are always arranged to the allocation center in sequence according to the distance first rule, resulting in some unreasonable allocation phenomena. In the future, we will consider studying the dynamic scheduling problem of multi variety medical supplies and multi service type distribution centers.

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References

[1]Liu Xin Research on the prediction and allocation method of emergency drug demand under sudden public health emergencies [D]. Xi'an University of Electronic Science and Technology, 2022.

[2] Jiang Xue Research on Emergency Material Allocation Considering Shortage Minimization in Sudden Public Health Incidents [D]. Southwest Jiaotong University, 2022.

[3] He Jin Optimization of urban emergency medical supplies allocation under sudden major epidemics [D]. Lanzhou Jiaotong University, 2023.

[4] Bai Dong Research on the allocation of emergency medical supplies and vehicle path planning under the background of the epidemic [D]. Beijing Jiaotong University, 2022.

[5] Li Yingzu Research on Optimization Design of Emergency Logistics Network for Sudden Epidemic Based on Service Level [D]. Nanjing University of Technology, 2020.

[6] Economou A, Fakinos D. A continuous-time Markov chain under the influence of a regulating point process and applications in stochastic models with catastrophes[J]. European Journal of Operational Research, 2003, 149(3):625-640.

[7] Büyüktahtakn I E, Des-Bordes E, Kibis E Y. A new epidemics–logistics model: Insights into controlling the Ebola virus disease in West Africa[J]. European Journal of Operational Research, 2018, 265(3): 1046-1063.

[8] Zhuang Yuanyuan, Zhang Keyong. Optimization of material allocation under public health events based on the SEIR model [J]. Journal of Shandong University (Science Edition), 2023,58 (03): 109-120

[9] Su Qiang, Lu Shuxiang. Multi stage emergency medical material dynamic allocation optimization model and algorithm [J]. Industrial Engineering and Management, 2022-27 (04): 50-57.

[10] Liu Ming, Cao Jie, Zhang Ding. Dynamic adjustment and optimization of data-driven epidemic emergency logistics network [J]. Systems Engineering Theory and Practice, 2020,40 (02): 437-448.

[11] Shang Xiaoting, Yang Kai, Zhang Guoqing, etc Dynamic Site Selection and Allocation Optimization of Designated Hospitals under COVID-19 Epidemic [J]. Control and Decision Making, 2023,38 (06): 1533-1540.