Research Article

Markov Decision Model of Emergency Medical Supply Scheduling in Public Health Emergencies of Infectious Diseases

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ABSTRACT

In this paper, a Markov decision process (MDP) model was established to study emergency medical material scheduling strategies for public health emergencies such as COVID-19. Within the constraints of dispatchable supplies, the priority of each medical node complicates the problem of deciding which hospital node supplies to respond to. The model assumes that the probability of events in the initial time period is in line with the Poisson distribution and that the location and priority of each hospital node is known when the material demand is initiated. The priority of hospital nodes is divided into four categories: critical, urgent, priority, and routine. There are several patients with different priorities in a hospital node: critical illness, severe illness, and mild illness. The priority of the hospital node is determined by the overall situation of the hospital patients. The MDP model established in this paper gives how to dispatch limited emergency medical supplies in the dispatching center to make the service rate of the whole system the best. The efficiency of the dispatching center in responding to the material needs of the hospital node depends on the constraints of the number and response time of different priority patients at the node. The maximum effect iterative dynamic model was simulated by simulation experiment and compared with the simulation effect under general conditions, so as to observe whether the model improved the system service rate.

1. INTRODUCTION

Public health emergencies refer to the sudden occurrence of major infectious diseases, food and occupational poisoning outbreaks, and other events that seriously affect public health. The term “emergency medical supplies” refers to all kinds of medical supplies that the government and society need to take emergency measures to protect lives and carry out rescues in emergencies. Due to the uncertainty of public health emergencies and the technical requirements of emergency medical supplies, the sudden shortage of a large number of specific types of emergency medical supplies often brings great difficulties to epidemic prevention and treatment [1].

Therefore, dispatching and allocating limited emergency medical supplies under sudden public health events is a special emergency material dispatch problem. The dispatch scheme of emergency medical supplies has a significant impact on controlling the development situation of medical events. According to the Chinese government’s emergency plan for public health emergencies, the government’s rules follow the principle of on-demand dispatch and distribution in the allocation of emergency supplies. This principle is fair but considering that the sudden public health events of infectious diseases such as COVID-19 virus are characterized by rapid spread, a wide range of infections, and great difficulty in prevention and control [2]. This scheduling principle is not effective in controlling the spread of the disease. In addition, the consumption of emergency medical supplies in the early stage of public health emergencies of infectious diseases is substantial. In the distribution of emergency supplies after disasters, there is an imbalance between supply and demand [3] because most emergency supplies are nondurable goods. It is difficult to maintain many stocks for them before the occurrence of low-probability disasters [4]. A timely supply of medical supplies is the key to rescuing patients and controlling the epidemic. In this case, it is imperative to allocate the limited resources reasonably to achieve better results. There are many studies on the allocation of emergency supplies, focusing on different aspects. Overall, the model goals [5–8] generally consider the maximization of the demand satisfaction rate, the minimization of emergency time, and the minimization of cost. The primary purpose is to reduce the cost of rescue as much as possible. However, for public health emergencies, such as infectious diseases, the most important thing is to control the epidemic quickly and ensure people’s lives to the greatest extent. Cost is not the core of our concern at this time. Making the best use of limited materials and controlling the epidemic’s spread effectively is the most critical

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problem. Therefore, this paper regards service rate maximization as the realization goal of our model, and the principle of material scheduling is based on the maximization of system efficiency. In the existing research on emergency management, most scholars consider completing one-time scheduling of emergency materials after emergencies [9,10]. This scheduling scheme is reasonable in general material scheduling but unreasonable for emergency medical materials under public health emergencies. Since the demand and material type constantly changes according to the variation in the epidemic situation, this paper applies a Markov decision model to study the continuous scheduling of emergency medical materials under public health emergencies.

Markov decision processes (MDP) are the optimal decision process of stochastic dynamic systems based on Markov process theory. The Markov property refers to the property that the probability law of the future development of a stochastic process has nothing to do with the history before observation. Bandara et al. [11] studied the optimal scheduling strategy in an emergency medical service (EMS) system and developed an MDP model to dispatch ambulances to patients optimally. They use the single-valued method to transform the initially developed continuous-time MDP into the equivalent discrete-time MDP and correctly consider the optimal decision-making strategy of each discrete-time element. The optimal scheduling strategy in EMS systems is studied while paying attention to the urgency of emergency calls. Based on their research, this paper divides the continuous-time Markov decision model into an equivalent continuous-time Markov decision model. According to the existing research experience, adopting a dynamic allocation model has apparent advantages in solving short-term shortages of consumption emergency materials. Kenneall et al. [12] developed a MDP model to study the air military medical evacuation dispatch policy in a combat environment. They classified casualties into three priority levels: emergency, priority, and routine. Multiple casualties can occur in one casualty event, and the casualty event with the highest priority determines the priority of the casualty event. Thus, we divided the priority of patients in designated hospitals into three categories: critical illness, severe illness, and mild illness. At the same time, considering the priority of the designated hospital, the number of types of patients, the required materials, and the position away from the dispatching center determine the hospital's priority. Simultaneously, they take the sum of the probability of Poisson distribution and the service rate of the region as the transition rate of the Markov decision model of the region. Based on them, we make improvements. Since the service rate in this paper is the service rate of the total system, the goal of the model is to maximize the system service rate. When the system service rate is poor, the epidemic situation will be more severe, and the number of hospitals that demand supplies will increase, so that the probability of the event will increase.

Based on the above research, this paper puts forward a Markov scheduling model, providing Markov decision-making scheduling for emergency medical materials under sudden public health events of infectious diseases and divides continuous MDP into equivalent discrete MDP. The model classifies patients and hospitals. By maximizing the system efficiency, the service rate of the system is enhanced. According to previous scholars, the transition probability is improved to be more in line with our research background.

2. LITERATURE REVIEW

In this section, we discuss the three most relevant literatures studied in this paper. They are (1) Emergent public health events, (2) Emergency material dispatch, and (3) Markov decision-making processes.

2.1. Emergent Public Health Event

The studies on public health emergencies are as follows: Zhu L et al. [13] approximately simulated the process of disaster diffusion by using infectious disease model. Aiming at major public health emergencies, Li Nan and others put forward the theory of “public opinion communication” with the government, media, and the public as the main body, and constructed the control mechanism of “public opinion communication” based on susceptible exposed infectious recovered (SEIR) infectious disease model. Liu et al. [15] discussed the location and personnel allocation of integrated temporary facilities for postdisaster humanitarian medical services, and provided an iterative method to obtain Pareto optimization. Yu Fying et al. [16] gave the layout model of emergency service facilities in infectious public health emergencies. Liu et al. [17] study how to effectively isolate patients when public health events similar to infectious diseases occur, in order to further control the epidemic situation. Garza et al. [18] apply lean thinking and constraint theory in peacetime scenarios to improve the operational efficiency of EMSs. Syahrir and Vanany [19] built a model to predict the number of drugs that hospitals have to provide when public health outbreaks occur in Indonesia in order to ensure the supply of drugs. He and Liu [20] based on the spread characteristics of the epidemic, pay attention to the distribution of single-variety medical materials, predict the medical needs of each region, and apply linear programming method to promote allocation decision-making. Hu Xiaowei [21] in view of the unreasonable dispatching of emergency medical materials and the low transfer efficiency of distribution centers in COVID-19 epidemic prevention and control, Hu Xiaowei redesigned the dispatching and distribution system of urban emergency medical materials under major public health emergencies, and gave the classification method of emergency medical materials.

2.2. Emergency Material Scheduling

Tian Jun [22] describes the demand for emergency materials with the help of triangular fuzzy numbers in fuzzy mathematics, simulates the real dynamic road network traffic condition by using continuous speed time dependence function, and establishes a multi-objective mathematical model for dynamic scheduling of emergency materials distribution. By designing the particle swarm optimization algorithm, using the “discrete-continuous vector hybrid coding” scheme and the weighted integrated fitness function guidance mechanism, combined with the continuously updated position and speed operation strategy, a fast and efficient algorithm for solving this kind of optimization model with the combination of discrete and continuous variables is established, which provides an effective and reliable method for the dynamic scheduling of material distribution under emergency conditions. Considering the problem of demand allocation and network allocation of emergency materials under fuzzy demand, Wang Haijun [23]...
establishes a network flow model aiming at minimizing the total distribution time. By using the gravity model algorithm and convex combination algorithm based on bilateral constraints, through the interactive iteration of the results of demand allocation and network flow allocation, the optimal demand allocation, path and network flow under the minimum total distribution time are obtained. Zhan Sha-lei et al. [24,25] use Bayesian analysis method to update the demand with historical experience data to establish the optimal material allocation time model. Guo Zixue [26] in order to improve the ability of rapid response to the demand for emergency materials, based on the characteristics of the emergency material scheduling problem, triangular fuzzy numbers are introduced to describe the uncertain attributes of emergency dispatching. The time minimization fuzzy optimization model of emergency material scheduling problem under triangular fuzzy information environment is established, and its equivalent fuzzy chance constrained programming model is given. Explore the deterministic transformation method of the model when the parameter is triangular fuzzy number, and verify the effectiveness of the transformation method through empirical case analysis. He Tilong [27] and others studied the scheduling problem of emergency materials from multiple rescue points to multiple demand points based on three kinds of road damage: feasible, repairable, and impassable. An optimal objective function is established, which takes into account the minimum total loading time and the lowest cost in the process of transportation, and the improved moth flaying swarm intelligent algorithm is used to solve the optimal emergency material scheduling scheme. Wang Hai-jun et al. [28] studied the dynamic supply of emergency materials for multimodal transport under the condition of uncertain supply and demand in the three-level emergency materials distribution network. In order to solve the problem of fairness and efficiency of material distribution in existing models, Zhou et al. [29] proposed a multi-objective dynamic scheduling model of emergency materials with matching supply and demand. Wang and Sun [30] also proposed a multi-stage dynamic scheduling model for emergency materials, but its research is different from the traditional method, using absolute shortage of materials to quantify fairness.

2.3. Markov Decision-Making Process

Zhan Sha-lei et al. [31] used MDP to establish a dynamic distribution model of emergency supplies for the dynamic distribution of emergency supplies in the environment of unbalanced supply and demand under typhoon disaster. According to the existing research experience, the dynamic distribution model has obvious advantages to solve the problem of short time supply shortage of expendable emergency supplies. Zhan Sha-lei et al. [31] for the dynamic allocation of emergency materials under typhoon disasters and the imbalance between supply and demand, the dynamic allocation model of emergency materials is established by using MDP. Regnier [32] successfully applied Markov decision-making method to weather forecast, hurricane path tracking, pre-disaster evacuation, and so on. Li Haonan [33] uses MDP to solve the problem of route selection in multi-mode traffic networks. Through a comprehensive analysis of the factors that affect travelers’ travel choice, a path decision model based on Markov decision method is constructed, an algorithm is designed, and an example is given to verify the feasibility of the proposed model and algorithm. Yang Feng [34] in view of the situation that the demand for emergency rescue materials in urban emergencies changes with the evolution of the accident, the demand for emergency rescue materials is designed as MDP, and a dynamic material allocation strategy is proposed. The decision-making model of rescue material demand is constructed and then optimized by flower pollination algorithm. Deng Xiaoping [35] based on the longitudinal kinematic characteristics of the following vehicle and the pilot vehicle, the MDP of the vehicle following process is established. Combined with the minimum safe distance model, an efficient, comfortable, and safe vehicle following decision algorithm is designed. Liang Feng [36] aims to maximize the profit of hospital inspection equipment, establishes a finite time domain MDP model, and combines the dynamic programming theory to obtain the optimal reservation scheduling strategy of the system. Considering the different quality of service parameters between different mobile terminals, Ning et al. [37] regards the vertical handoff decision problem as a MDP, establishes an incentive function with the goal of maximizing the expected total return and minimizing the average handoff times, evaluates the service quality of each link, and obtains a stable and deterministic handoff decision strategy. Talluri and Van Ryzin [38] and others take customer selection behavior as the research background, construct the MDP model, take the nested allocation strategy as the optimal strategy, and prove that the model and the estimation process are effective. Schütz [39] aiming at the problem of examination resource allocation among different types of patients, a continuous-time MDP is established to consider the randomness of equipment service time and the unpunctual factors of some patients, and the optimization goal is to obtain the maximum benefit for the hospital, which is solved by the method of approximate dynamic programming. Zhuang and Li [40] uses the MDP model to study how to distribute multiple examination equipment among the three types of patients in order to maximize benefits on the day of service.

3. MDP MODEL OF EMERGENCY MEDICAL SUPPLIES DISPATCHING

In this section, the MDP model and the required parameters and related model components are described. Finally, the optimal equation of the MDP for medical material scheduling in this paper is given.

3.1. Model Description

The materials that can be raised in a certain period under sudden public health events are limited; that is, the materials that can be dispatched by the model in a specific time are limited. According to the time required for dispatching materials, the system time is discretized and divided into segments with time length D, which are represented by Dn. At this time, the material demand in Dn is processed in Dn+1. Nodes that did not respond in the previous time accumulate to respond in the later period.

A specific amount of time is needed for the system to receive and respond to the requirements of a node hospital, which is defined as the response time T. The response process can be disassembled into the following key links: (1) the scheduling time of personnel and materials D; (2) the transportation time of the materials T.
3 the potential time delay $T_i$; and 4 the unloading distribution time $T_m$.

$$T_i = D + T_j + T_k + T_m$$

After the dispatching center responds to the nodes with requirements, the transport team returns to the dispatching center to complete a service. $T_i$ Represents service time and $E_i$ return time.

$$T_i = T_i + E_i$$

### 3.2. Model Formulation

This section introduces the MDP model formula used to determine the emergency medical material dispatching strategy under the public health emergencies of infectious diseases. The MDP model is designed to determine how to conduct material scheduling in the case of limited materials for requests in a given node network to maximize the response efficiency of the node network. We make it a general dispatching principle that the dispatching center distributes the material needs of nodes according to the order in which material requests are made.

For the model in this article, the following parameters need to be provided.

$I = \{1, 2, \ldots, i\}$ is the node hospital in the system, where $i < \infty$.

$a_{ij}^{D_D}$ represents the node hospital that initiates the material request at time $D_n$ in the system, $a_{ij}^{D_D} \subseteq I$.

$b_{ij}^{D_D}$ represents the node hospital that initiates the material request according to $\rho_i$ at time $D_n$ in the system, $b_{ij}^{D_D} \subseteq a_{ij}^{D_D}$.

$c_{ij}^{D_D}$ represents the node hospital that initiates the material request at time $D_n$ in the system and is responded, $c_{ij}^{D_D} \subseteq b_{ij}^{D_D}$.

$d_{ij}$ stands for the distance between node i and node j.

$M_{ij}^{D_D}$ stands for the total amount of materials required by node i.

$M_D$ stands for the materials that can be dispatched by the dispatching center within D period of time.

$\rho_i$ is the probability of occurrence of node hospital i events in the system, which is obtained by comprehensive consideration of Poisson's probability $\lambda_i$ and the efficiency of the node.

$h$ represents the classification of patients, $h \in \{1, 2, 3\}$, $h = 3$ means that the patient is critically ill, $h = 2$ means that the patient is severe case, $h = 1$ means that the patient is mildly ill.

$\mu_i$ is the priority of each node hospital, $\mu = 1, \mu = 2, \mu = 3, \mu = 4$, corresponding to level 1, level 2, level 3, and level 4 responses respectively.

$\delta_{h\mu}^{D_D}$ is the proportion of node hospitals with priority $\mu$ in hospitals at the moment $D_n$, so $\sum_{\mu=1}^{4} \delta_{h\mu}^{D_D} = 1$. The setting of response level is divided by reference to the setting of response level in the emergency plan of public health emergencies published in the region, and the judgment of response level is based on quantitative and qualitative methods.

$\psi_{ih}^{D_D}$ dispatch center is the immediate effect obtained on patients with different priority within node hospital i, $he (0, 1, 2, 3)$.

$\phi_{ih}^{D_D}$ is the total efficiency of material request response proposed by the dispatching center for node hospital i, which is adjusted by time $\Lambda$. The model will calculate the node total efficiency of the material demand proposed by $D_n$ in the period, and select the node of the expected service.

The model assumes whether the reaction is based on the response level of the node, the material scheduling situation, and the distance between the node's hospital and the dispatching center. We have considered that the assumption of an exponential distribution of node event arrival probability is unreasonable. Computational experiments by Jarvis [41] show that the behavior of the system we are modeling is relatively insensitive to the shape of the service time distribution. Gross and Harris [42] also provide well-known insensitive results. McLay and Mayorga [43] performed simulation analysis to compare the use of exponentially distributed service times with more realistic service times. They found that the assumption of index service time did not significantly affect the optimal strategy. Considering that our model is quite different from theirs, our model has a feedback mechanism; that is, the response effect in the last period affects the event arrival probability of the system in the next period, so we include the response effect, namely, the service efficiency, in the calculation of the event arrival probability. The service rate refers to the ratio between the efficiency obtained by the system in $D_n$ and the maximum efficiency of the system at this time. Then, the optimal efficiency is the ratio between the efficiency obtained by the model in $D_n$ and the maximum efficiency of the system at this time, and the general efficiency is the ratio between the efficiency obtained in $D_n$ according to the general scheduling principle and the maximum efficiency of the system at this time.

The MDP model components are described as follows:

**State-space:** $S = S_1 \times S_2 \times \cdots \times S_n$, which represents the state space of the system, and $S_D$ represents the state of node $a_i$ at time D. Considering that a hospital with response level 4 is responded to, we obtain its state, $S_D^4 = \{4, 1\}$.

**State-space table:**

| State | Setting |
|-------|---------|
| $\mu$ | $\{1, 2, 3, 4\}$ |

**Action space:** The action of whether to respond is indicated by $\nu_i$, $\nu = 1$ corresponding to a response and $\nu = 0$ means lack of response. The decision made by the current system is to decide which node hospitals to respond to after receiving a request from a node hospital in the network within the period $D_n$. Let $B \left( a_{ih}^{D_D} \right)$ represent the set of nodes i that are in state S in period $D_n$ and propose material requirements.

The model allows nodes that have not been processed in the previous period to join in this stage. $a_{ih}^{D_D}$ indicates the node to be responded to within the period; then, $a_{ih}^{D_D} = a_{ih}^{D_D} + \mu_{ih}^{D_D}$. We set the response probability of the hospital with the highest priority at 1.
State transition probability matrix

$P_i$ is the transition probability matrix related to $v_i$, and the size is $4 \times 4$. $[P_i]_j$ represents the transition probability of the node from state $s_i$ to each state in state-space $S$ under given conditions, whether the node hospital responds to it at priority $\mu$, and the transition to the probability of other priorities is a $1 \times 4$ vector.

$P_i((m|s, v_i))$ is an element in $P_i$, which represents the transition probability of the node hospital from state $s$ to state $m$ under action $v_i$.

$$P_i = \begin{bmatrix}
[P_i]_1 \\
[P_i]_2 \\
[P_i]_3 \\
[P_i]_4
\end{bmatrix}$$

The $P_h$ patient transfers to another priority state transition matrix after being rescued, and the size is $4 \times 4$. Our model assumes that the patient's condition does not deteriorate after receiving assistance and may remain as it is or shift to a lower priority.

$[P_h]_h$ is the transition probability of the patient from priority $h$ to other priorities when the node responds, and it is a $1 \times 4$ vector. $P_h((H|h))$ is an element in $P_h$, representing the transition probability of the patient from priority $h$ to priority $H$.

$$P_h = \begin{bmatrix}
[P_h]_0 \\
[P_h]_1 \\
[P_h]_2 \\
[P_h]_3
\end{bmatrix}$$

Priority: The hospital response level $\mu_i$ is obtained by providing a comprehensive evaluation.

$$\mu_i = \left[ f(u_Q, u_h) + \frac{1}{2} \right]$$

$u_Q$ is the priority of expert evaluation, $u_Q = \sum \mu_i^D / Q$. We take the number of different types of patients in the hospital, the distribution of materials, the distance between the hospital and the Red Cross Society, and other related statistical data as a reference to make an expert score table for $Q$ experts to review and each expert gives the response level $\mu_i^D$ of the node in time $D_n$, and then carries out a weighted average to get the priority level of each hospital.

$u_h = g_h^1, g_h^2$ represents the proportion of different types of patients in the whole node hospital, $h$ is the classification of patients, and $h \in (0, 1, 2, 3)$.

Efficiency: When the dispatching center responds to the material request put forward by node $a_i$ with response level $\mu_i$ in the network within a period $D_n$, the system obtains a service effect $\varphi^D_i$. The effect depends on the number of patients in different categories, the distribution of materials, and the distance between the hospital and the Red Cross Society.

When the material demand proposed by node $a_i$ is responded to by the dispatching center, an effect is immediately obtained for patients with different priority $h$, defined as $\psi_h, \sum \psi_h = 1$. We define $\psi_i^D$ as the immediate effect of node $i$ in patients of various priorities.

$$\psi_i^D = \sum_{h=1}^{4} \psi_h \cdot g_h^i$$

We define $\psi_h$ as the effect of treating a single patient, $k \in \{1, 2, 3, 4, 5, 6\}$, which represent the effect of converting $h$ from 3 to 2, h from 2 to 1, h from 1 to 0, h from 3 to 1, h from 2 to 0, h from 3 to 0, so $\sum_{h=1}^{6} \psi_h = 1. \psi_1 = \psi_2 = \psi_3 = \psi_4 = 1$. We add a penalty item to the effect of each node to ensure that some node hospitals in the system do not turn into worse situations. When the total time from node $a_i$’s request to the network's response exceeds $A$, we add a penalty factor to punish the efficiency generated by the dispatching center’s response to node $a_i$’s request. At this time, the efficiency that the network can obtain at node $a_i$ is also the maximum efficiency $\varphi^D_i$ that the system can obtain at $a_i$.

$$\varphi^D_i = \psi_i^D - \sigma L \{ T_i > A \}, \sigma < \infty$$

$L \{ T_i \leq A_i \}$ is an indicator variable. When the condition $T_i > A$ is achieved, or when the response time exceeds $A$, the value is 1. When the response time is within $A$, the value is 0. $\sigma$ is a penalty factor for efficiency and is a sufficiently large positive number.

Transition state: $\rho_i$ is the event arrival probability of node $i$ in the network. In the general model, the probability of event arrival obeys a Poisson distribution; that is, the probability of event arrival at node $a_i$ is the Poisson probability $\lambda_i$. Considering that our model has a feedback mechanism, the service rate has a significant impact on the development of events. Therefore, we revise the utilization service rate $\phi$ of $\lambda_i$ and obtain the revised $\rho_i$. Of course, when the system response effect is good, the service rate is high, and the probability of system events in the next period should be reduced.

$$\rho_i = \begin{cases} 
\lambda_i / \phi & \text{if } D > 1 \\
D = 1
\end{cases}$$

Optimality equation

$$J_{D_n} = \rho_i \psi_i^D \max \left( \varphi_i^D + \sum_{h=1}^{6} \frac{1}{\psi_h} \cdot \mu^h \right)$$

$$\varphi^D_i = \sum_{h=1}^{4} \psi_h^D - \sigma L \{ T_i > A \}, \sigma < \infty$$
\[i \in \Gamma_i^D,\]
\[\sum M_i \leq M_D\]

4. DATA SIMULATION EXPERIMENT

In this section, we apply the MDP model developed in the previous section to Wuhan city under lockdown management due to the COVID-19 epidemic.

4.1. Model Parameters

We set up an application scenario for the model and provided an emergency medical supply scheduling scheme for the designated hospitals that treated patients in Wuhan, closed during the novel coronavirus pneumonia epidemic. City closure management means that to do an excellent job in preventing and controlling pneumonia in novel coronavirus and effectively cut off the route of virus transmission. Since 10:00 on January 23, the city bus, subway, ferry, and long-distance passenger transport in Wuhan have been suspended. Without special reasons, citizens cannot leave Wuhan, and there is a temporary closure of the airport and railway station from Han. According to the government documents of Wuhan Municipal Government and the epidemic prevention and control department, during the epidemic prevention and control period, designated hospitals in Wuhan mainly treated patients with novel coronavirus were divided into five batches, among which the fourth and fifth batches were specially treated for suspected cases transferred from the previous three batches of designated hospitals. Therefore, the system only carries out simulation on 24 hospitals in the first three batches. On January 27, the press conference of the Wuhan epidemic situation said that fundraising was unified and centralized, and donations were only accepted through provincial and municipal Red Cross Societies. Therefore, the Wuhan Red Cross Society was taken as the systematic material dispatching center.

Twenty-four designated hospitals are numbered, and the numbering sequence is listed in Table 1 below.

According to Baidu Map navigation, the shortest driving distance between each designated hospital and the Red Cross Society and the time required for driving at this time are obtained, as displayed in Table 2. As the Wuhan municipal government has carried out road control in the city, it is not affected by traffic factors (traffic lights and jams) in general, so we take the highest driving speed in the shortest route as the simulated average driving speed.

According to official statistics, as of 24:00 on February 10, 2020, Hubei Province reported 31,728 cases of pneumonia in COVID-19, including 18,454 cases in Wuhan, and 974 cases died in the province, with a fatality rate of 3.07%, including 748 cases in Wuhan with a fatality rate of 4.05%. According to the relevant news reports during the epidemic, when all sectors of society donate materials to the Wuhan Red Cross Society, the unloading time of all kinds of materials is usually computed by tons: the unloading time per unit of materials is accumulated, and the unloading time per unit of materials is 10 minutes. The error time is controlled within 0–60 minutes, and random error is made for each point by Python. As the number of patients and materials mentioned above are too large and the scales are not uniform, the data are uniformly processed, the number of people is equivalent to 0–50, and the number of materials is equivalent to a number in m. The materials needed by each designated hospital are within 0–10 m, and the number of materials that can be dispatched within d is 50 m. Scheduling time d is set to 360 minutes (6 hours). Each designated hospital’s priority calculation process is not detailed in this section but is directly given in the table.

| Hospital                              | Wuhan Hankou hospital | Wuhan red cross hospital | Wuhan Seventh Hospital | Wuhan No.4 hospital west yard area | Wuhan Ninth Hospital | Wuhan Wuhan hospital | Wuhan Wuhan hospital | Wuhan Wuhan hospital |
|---------------------------------------|-----------------------|--------------------------|------------------------|-----------------------------------|----------------------|----------------------|----------------------|----------------------|
| i Hospital                            | 1                     | 2                        | 3                      | 4                                  | 5                    | 6                     | 7                    | 8                    |
| Hospital                              | Wuhan No.5 Hospital   | Central hospital of wuhan Houhu Campus | Wuhan No.3 Hospital Guanggu Campus | Wuhan WISCO Second Hospital | Huazhong University of Science and Technology Affiliated tongji hospital Sino-French New City Campus | Wuhan union medical college hospital west area | Hubei provincial people’s hospital east yard | Hubei Provincial Hospital of Integrated Traditional Chinese and Western Medicine |
| i Hospital                            | 7                     | 8                        | 9                      | 10                                 | 11                   | 12                   | 13                   | 14                   |
| Hospital                              | Hubei liuqier combination of Chinese traditional and western medicine orthopedics hospital | Hubei Provincial Hospital of Integrated Traditional Chinese and Western Medicine | Tianyou Hospital Affiliated to Wuhan University of Science and Technology | Wuhan No.6 Hospital | Wuhan traditional Chinese medicine hospital hanyang branch | Wuhan Zijing hospital | Wuhan Union hospital | Wuhan Zijing hospital |
| i Hospital                            | 14                    | 15                       | 16                     | 17                                 | 18                   | 19                   | 20                   | 21                   |
| Hospital                              | Wuhan Xinzhou district traditional Chinese medicine hospital | Wuhan caidian district Mater- nal and Child Health Hospital | Wuhan huangpi district traditional Chinese medicine hospital | Wuhan qiaoya boai recovery hospital | Wuhan hannah district traditional Chinese medicine hospital | Wuhan Zijing hospital | Wuhan Zijing hospital | Wuhan Zijing hospital |

Table 1 | Hospital number table.
Different priorities of patient treatment immediately affect the following equation:

$$\psi_1 = 0.2, \psi_2 = 0.3, \psi_3 = 0.5$$

Different types of patient treatment effects:

$$\psi_1 = 0.5, \psi_2 = 0.3, \psi_3 = 0.2, \psi_4 = 0.8, \psi_5 = 0.5, \psi_6 = 1$$

Effect of different priorities:

$$c_1 = \mu (\mu = 1), c_2 = 2 \mu = 2, c_3 = 3 (\mu = 3), c_4 = 4 (\mu = 4)$$

The penalty time in the system is set to 1590 minutes (26.5 hours). From the state transition matrix, the probability of maintaining the original priority is the highest when the hospital that puts forward the urgent medical supplies demand within D is responded, thus, the situation does not noticeably deteriorate if it is not responded within D. Considering the extremely infectious characteristics of the novel coronavirus, and according to relevant news reports, during the epidemic prevention and control period, many hospitals were infected due to the lack of emergency medical materials such as masks and protective clothing, greatly reducing the rescue efficiency of the hospital. We assume that the emergency medical supply-demand of a designated hospital in two consecutive days has never been met, and the treatment situation becomes terrible. The calculation of specific data is based on the calculation equation of response time:

$$T_i = D + T_0 + T_e + T_m$$

Scheduling time is 360 minutes, maximum driving time is 95 minutes, maximum error time is 60 minutes, and maximum unloading time is 100 minutes, so the longest response time of two consecutive periods is 1230 minutes (28.5 hours), and the demands put forward in the previous stage is processed in the next stage, so A = 1590 minutes (26.5 hours).

### 4.2. Simulation Results and Optimal Strategy

This section only presents the simulation data of four time periods D and the scheduling results of the model. The number of designated hospitals that put forward material demand in period \(D_1\) is calculated by using \(\rho_1\) after being randomly selected four times by Python. The specifically designated hospitals and the order in which they put forward material requirements are randomly selected.

The rescue efficiency, total expected efficiency, and expected response time of 10 designated hospitals on different patients were calculated. As shown in Table 4, the red mark is the expected effect of the designated hospital that has not responded under the maximum efficiency. In contrast, the blue mark is the designated hospital’s expected efficiency that has not responded under general efficiency. The service rate under optimal efficiency is defined as \(\varphi_m\), and the service rate for general efficiency is \(\varphi_n\):

Based on the optimality equation:

$$J_{D_n} = \rho \frac{D_n}{\mu} \max \left( \sum \varphi_{D_n}, \sum \frac{1}{\psi_n} \psi_{D_n} P_{D_n} I_{D_n} \right)$$

In general, the efficiency is 582.89, the materials used and 47 m, the remaining 3 m, \(\varphi_1 = 0.635\).

Choice for designated hospitals: 8, 22, 2, 1, 7, 4, 6, 14, 21.
The system had a maximum efficiency of 917.93, an optimal efficiency of 860.81, \( \phi_{i1} = 0.938 \), and the following materials were employed:

System choice for designated hospitals, numbers 4, 6, 7, 8, 14, 15, 21, and 22

Points that have not responded under different internal efficiencies of \( D_i \) are incorporated into the above table, in which the red marks are designated hospitals that have not responded under the optimal efficiency of the system, and the blue marks are designated hospitals that have not responded under the general efficiency of \( D_i \). By default, the demand arrival order of these three hospitals is the first in \( D_2 \).

The current material in \( D_2 \) is 53 m, and the remaining material in \( D_1 \) is 3 m, so the general efficiency of \( D_2 \) is 1415.66. At this time, the maximum efficiency of the system is 1814.25. At 50 m, \( \phi_2 = 0.78 \). The materials used are 50 m and the remaining 3 m.

The designated hospitals selected by the service system are numbered 2, 3, 22, 4, 13, 10, 15, 8, 12, and 16.

The expected response time of the two schemes is not more than A, and the peak efficiency that the system can obtain is the optimal efficiency of the system.

The system had a maximum efficiency of 917.93, an optimal efficiency of 860.81, \( \phi_{i1} = 0.938 \), and the following materials were employed:

System choice for designated hospitals, numbers 4, 6, 7, 8, 14, 15, 21, and 22

Points that have not responded under different internal efficiencies of \( D_i \) are incorporated into the above table, in which the red marks are designated hospitals that have not responded under the optimal efficiency of the system, and the blue marks are designated hospitals that have not responded under the general efficiency of \( D_i \). By default, the demand arrival order of these three hospitals is the first in \( D_2 \).

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The designated hospitals selected by the service system are numbered 2, 3, 22, 4, 13, 10, 15, 8, 12, and 16.

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System choice for designated hospitals, numbers 4, 6, 7, 8, 14, 15, 21, and 22

Points that have not responded under different internal efficiencies of \( D_i \) are incorporated into the above table, in which the red marks are designated hospitals that have not responded under the optimal efficiency of the system, and the blue marks are designated hospitals that have not responded under the general efficiency of \( D_i \). By default, the demand arrival order of these three hospitals is the first in \( D_2 \).

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The designated hospitals selected by the service system are numbered 2, 3, 22, 4, 13, 10, 15, 8, 12, and 16.

The expected response time of the two schemes is not more than A, and the peak efficiency that the system can obtain is the optimal efficiency of the system.

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System choice for designated hospitals, numbers 4, 6, 7, 8, 14, 15, 21, and 22

Points that have not responded under different internal efficiencies of \( D_i \) are incorporated into the above table, in which the red marks are designated hospitals that have not responded under the optimal efficiency of the system, and the blue marks are designated hospitals that have not responded under the general efficiency of \( D_i \). By default, the demand arrival order of these three hospitals is the first in \( D_2 \).

The current material in \( D_2 \) is 53 m, and the remaining material in \( D_1 \) is 3 m, so the general efficiency of \( D_2 \) is 1415.66. At this time, the maximum efficiency of the system is 1814.25. At 50 m, \( \phi_2 = 0.78 \). The materials used are 50 m and the remaining 3 m.

The designated hospitals selected by the service system are numbered 2, 3, 22, 4, 13, 10, 15, 8, 12, and 16.

The expected response time of the two schemes is not more than A, and the peak efficiency that the system can obtain is the optimal efficiency of the system.

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System choice for designated hospitals, numbers 4, 6, 7, 8, 14, 15, 21, and 22

Points that have not responded under different internal efficiencies of \( D_i \) are incorporated into the above table, in which the red marks are designated hospitals that have not responded under the optimal efficiency of the system, and the blue marks are designated hospitals that have not responded under the general efficiency of \( D_i \). By default, the demand arrival order of these three hospitals is the first in \( D_2 \).

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The designated hospitals selected by the service system are numbered 2, 3, 22, 4, 13, 10, 15, 8, 12, and 16.

The expected response time of the two schemes is not more than A, and the peak efficiency that the system can obtain is the optimal efficiency of the system.

The system had a maximum efficiency of 917.93, an optimal efficiency of 860.81, \( \phi_{i1} = 0.938 \), and the following materials were employed:

System choice for designated hospitals, numbers 4, 6, 7, 8, 14, 15, 21, and 22

Points that have not responded under different internal efficiencies of \( D_i \) are incorporated into the above table, in which the red marks are designated hospitals that have not responded under the optimal efficiency of the system, and the blue marks are designated hospitals that have not responded under the general efficiency of \( D_i \). By default, the demand arrival order of these three hospitals is the first in \( D_2 \).

The current material in \( D_2 \) is 53 m, and the remaining material in \( D_1 \) is 3 m, so the general efficiency of \( D_2 \) is 1415.66. At this time, the maximum efficiency of the system is 1814.25. At 50 m, \( \phi_2 = 0.78 \). The materials used are 50 m and the remaining 3 m.

The designated hospitals selected by the service system are numbered 2, 3, 22, 4, 13, 10, 15, 8, 12, and 16.

The expected response time of the two schemes is not more than A, and the peak efficiency that the system can obtain is the optimal efficiency of the system.

The system had a maximum efficiency of 917.93, an optimal efficiency of 860.81, \( \phi_{i1} = 0.938 \), and the following materials were employed:

System choice for designated hospitals, numbers 4, 6, 7, 8, 14, 15, 21, and 22

Points that have not responded under different internal efficiencies of \( D_i \) are incorporated into the above table, in which the red marks are designated hospitals that have not responded under the optimal efficiency of the system, and the blue marks are designated hospitals that have not responded under the general efficiency of \( D_i \). By default, the demand arrival order of these three hospitals is the first in \( D_2 \).

The current material in \( D_2 \) is 53 m, and the remaining material in \( D_1 \) is 3 m, so the general efficiency of \( D_2 \) is 1415.66. At this time, the maximum efficiency of the system is 1814.25. At 50 m, \( \phi_2 = 0.78 \). The materials used are 50 m and the remaining 3 m.

The designated hospitals selected by the service system are numbered 2, 3, 22, 4, 13, 10, 15, 8, 12, and 16.

The expected response time of the two schemes is not more than A, and the peak efficiency that the system can obtain is the optimal efficiency of the system.
Table 7 | OE Simulation data of \( D_2 \).

| i | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|----|----|----|----|----|
| order | 1 | 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| \( \mu \) | 2 | 1 | 3 | 4 | 2 | 2 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 |
| \( M_i \) | 4 | 2 | 6 | 9 | 6 | 7 | 3 | 4 | 5 | 3 | 3 | 2 | 2 | 1 |

Table 8 | GE of \( D_2 \).

| i | 15 | 10 | 18 | 17 | 3 | 11 | 14 | 5 | 19 | 7 | 1 | 6 | 16 |
|---|----|----|----|----|---|----|----|---|----|---|---|---|---|
| \( \mu \) | 4 | 2 | 1 | 3 | 2 | 2 | 4 | 4 | 2 | 3 | 1 | 2 | 1 | 2 |
| \( \phi_i \) | 143 | 50.4 | 19.4 | 76.2 | 55.6 | 50.6 | 148 | 154.8 | 45.6 | 72.3 | 91.2 | 17.3 | 52.2 |
| \( \phi_e \) | 123.72 | 43.82 | 15.97 | 69.06 | 47.70 | 44.04 | 125.20 | 131.76 | 38.78 | 64.59 | 75.78 | 14.11 | 42.52 |
| \( \phi_m \) | 29.66 | 15.70 | 17.69 | 24.21 | 17.22 | 47.32 | 57.31 | 57.31 | 42.19 | 15.21 | 20.87 | 10.47 | 10.52 |

Table 9 | OE of \( D_2 \).

| i | 2 | 1 | 3 | 22 | 4 | 13 | 10 | 15 | 8 | 12 | 16 |
|---|---|---|---|----|---|----|----|----|---|----|----|
| \( \mu \) | 2 | 1 | 3 | 4 | 2 | 2 | 1 | 2 | 1 | 2 | 1 |
| \( \phi_i \) | 26 | 5.8 | 111 | 161 | 55.6 | 59 | 19 | 55.8 | 24.7 | 39.2 | 11.4 |
| \( \phi_e \) | 20.62 | 4.67 | 95.13 | 136.84 | 51.46 | 51.46 | 16.56 | 48.14 | 21.78 | 31.78 | 9.38 |
| \( \phi_m \) | 11.66 | 5.24 | 34.31 | 33.12 | 17.69 | 47.32 | 17.55 | 11.85 | 25.99 | 9.30 | 23.66 |

Table 10 | GE response time of \( D_2 \).

| i | 15 | 10 | 18 | 17 | 3 | 11 | 14 | 5 | 19 | 7 | 1 | 6 | 16 |
|---|----|----|----|----|---|----|----|---|----|---|---|---|---|
| \( D \) | 720 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 |
| \( T_{ij} \) | 17 | 36 | 9 | 21 | 14 | 31 | 7 | 18 | 9 | 12 | 9 | 12 | 5 |
| \( T_e \) | 90 | 60 | 20 | 60 | 20 | 20 | 50 | 50 | 10 | 90 | 80 | 30 | 30 |
| \( T_m \) | 60 | 37 | 9 | 44 | 25 | 29 | 39 | 43 | 17 | 42 | 26 | 14 | 17 |
| \( T_i \) | 857 | 493 | 398 | 485 | 419 | 440 | 456 | 471 | 406 | 504 | 475 | 417 | 412 |

The designated hospitals selected for service are numbered 7, 1, 16, 6, 14, 13, 12, 9, 4, 21, and 18.

In \( D_3 \), the maximum efficiency of the system is 1407.05, the optimal efficiency is 1380.02, and \( \varphi_3 = 0.98 \), when all materials are applied.

The designated hospitals selected by the service system are numbered 4, 9, 16, 10, 3, 2, 17, and 7, respectively.

The expected response time of the two schemes is not more than \( A \), and the ideal efficiency that the system can obtain is the optimal efficiency of the system.

According to the transition rate \( \rho_i \) adjusted by \( \varphi_3 = 0.728, \varphi_3 = 0.98 \). \( D_4 \) computed that the number of designated hospitals that proposed material requirements under general efficiency is 11, and...
the number of designated hospitals that proposed material requirements under optimal efficiency is 8. The relevant data are described as follows.

However, the unresponsive points in $D_3$ with different efficiencies are incorporated into Table 19, and by default, the demand arrival order of these five hospitals ranks first in $D_4$. 

### Table 12 | GE Simulation data of $D_3$.  

| i  | 7 | 1 | 16 | 13 | 12 | 9 | 21 | 18 | 20 | 19 |
|----|---|---|----|----|----|---|----|----|----|----|
| $\mu_i$ | 3 | 3 | 2 | 4 | 4 | 1 | 2 | 3 | 1 | 2 | 1 | 4 | 3 | 2 |
| $\phi_i$ | 72.3 | 91.2 | 52.2 | 144 | 152 | 7.8 | 63.2 | 100.2 | 11.2 | 29.2 | 12.1 | 156 | 95.7 | 47.2 |
| $\phi_e$ | 64.59 | 75.78 | 42.52 | 126.56 | 134.80 | 6.58 | 54.92 | 87.60 | 9.78 | 22.98 | 10.39 | 135.48 | 82.77 | 38.90 |

### Table 13 | OE Simulation data of $D_3$.  

| i  | 1 | 4 | 9 | 16 | 10 | 3 | 2 | 12 | 17 | 7 |
|----|---|---|----|----|----|---|----|----|----|----|
| $\mu_i$ | 1 | 2 | 4 | 4 | 3 | 1 | 2 | 4 | 3 | 1 |
| $\phi_i$ | 5.8 | 45.4 | 161 | 152 | 93 | 8.9 | 43.6 | 147.2 | 90.9 | 9 |
| $\phi_e$ | 4.67 | 38.52 | 139.48 | 129.72 | 79.53 | 7.01 | 36.22 | 128.96 | 78.33 | 8.01 |
| $\phi_m$ | 5.24 | 11.99 | 33.36 | 35.22 | 34.52 | 7.96 | 15.96 | 34.52 | 28.21 | 5.67 |

### Table 14 | GE of $D_3$.  

| i  | 7 | 1 | 16 | 13 | 12 | 9 | 4 | 21 | 18 | 8 | 20 | 19 |
|----|---|---|----|----|----|---|----|----|----|----|----|----|
| $\mu_i$ | 3 | 3 | 2 | 4 | 4 | 1 | 2 | 3 | 1 | 2 | 1 | 4 | 3 | 2 |
| $\phi_i$ | 720 | 720 | 720 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 |
| $\phi_e$ | 90 | 80 | 30 | 90 | 90 | 20 | 80 | 50 | 40 | 30 | 60 | 60 | 70 |
| $\phi_m$ | 20 | 70 | 25 | 20 | 50 | 20 | 60 | 30 | 20 | 50 | 60 | 30 |

### Table 15 | OE of $D_3$.  

| i  | 1 | 4 | 9 | 16 | 10 | 3 | 2 | 12 | 17 | 7 |
|----|---|---|----|----|----|---|----|----|----|----|
| $\mu_i$ | 1 | 2 | 4 | 4 | 3 | 1 | 2 | 4 | 3 | 1 |
| $\phi_i$ | 5.8 | 45.4 | 161 | 152 | 93 | 8.9 | 43.6 | 147.2 | 90.9 | 9 |
| $\phi_e$ | 4.67 | 38.52 | 139.48 | 129.72 | 79.53 | 7.01 | 36.22 | 128.96 | 78.33 | 8.01 |
| $\phi_m$ | 5.24 | 11.99 | 33.36 | 35.22 | 34.52 | 7.96 | 15.96 | 34.52 | 28.21 | 5.67 |

### Table 16 | GE response time of $D_3$.  

| i  | 7 | 1 | 16 | 13 | 12 | 9 | 4 | 21 | 18 | 8 | 20 | 19 |
|----|---|---|----|----|----|---|----|----|----|----|----|----|
| $\mu_i$ | 3 | 3 | 2 | 4 | 4 | 1 | 2 | 3 | 1 | 2 | 1 | 4 | 3 | 2 |
| $\phi_i$ | 720 | 720 | 720 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 |
| $\phi_e$ | 90 | 80 | 30 | 90 | 90 | 20 | 80 | 50 | 40 | 30 | 60 | 60 | 70 |
| $\phi_m$ | 20 | 70 | 25 | 20 | 50 | 20 | 60 | 30 | 20 | 50 | 60 | 30 |

### Table 17 | OE response time of $D_3$.  

| i  | 1 | 4 | 9 | 16 | 10 | 3 | 2 | 12 | 17 | 7 |
|----|---|---|----|----|----|---|----|----|----|----|
| $\mu_i$ | 1 | 2 | 4 | 4 | 3 | 1 | 2 | 4 | 3 | 1 |
| $\phi_i$ | 5.8 | 45.4 | 161 | 152 | 93 | 8.9 | 43.6 | 147.2 | 90.9 | 9 |
| $\phi_e$ | 4.67 | 38.52 | 139.48 | 129.72 | 79.53 | 7.01 | 36.22 | 128.96 | 78.33 | 8.01 |
| $\phi_m$ | 5.24 | 11.99 | 33.36 | 35.22 | 34.52 | 7.96 | 15.96 | 34.52 | 28.21 | 5.67 |

the number of designated hospitals that proposed material requirements under optimal efficiency is 8. The relevant data are described as follows.
The general efficiency of $D_4$ is 1319.41. At this time, the maximum efficiency of the system is 1589.01, $\varphi_4 = 0.830$, and the material usage is 49 m. The designated hospitals selected for service are numbered 8, 20, 19, 5, 23, 10, 9, 14, 1, 17, and 18.

The maximum efficiency of the system at $D_4$ is 1129.20, and according to the principle of maximizing efficiency, the optimal efficiency is 1118.73. At this time, all materials were used, but the expected response time of unresponsive designated hospital 1 at this time was 1495 minutes. If it is decided whether to respond until $D_5$, according to the optimal equation, the model penalizes the system efficiency and affects the overall effectiveness. Therefore, we respond to it at this stage. At this time, the optimal efficiency of the system is 1112.19, $\varphi_4 = 0.985$, and 49 m of materials are used at this time, with a balance of 1 m to $D_5$.

The designated hospitals selected by the service system are numbered 1, 8, 12, 4, 18, 17, 3, 9, and 21.

### 4.3. Discussion of Simulation Result

The result analysis shows that when the optimal strategy is applied to the medical material scheduling system, the response to the material request of the designated hospital is mainly determined by the priority of the designated hospital and the efficiency of the material unit. By comparing the simulation data of the four stages, it can be seen that when the optimal strategy is applied to the medical material scheduling system, the service rate of the system in the four stages is much higher than that in general. Under the optimal strategy, the service rate of the system in four stages is close to one, which basically meets the overall material demand of the system at the current stage, while the maximum service rate under the general strategy is only 0.83, as shown in Figure 1. Although there are designated hospitals under the optimal strategy, their response time is much longer than other designated hospitals. The model added a time constraint based on optimal efficiency to avoid the rapid deterioration of the epidemic situation in such designated hospitals due to the lack of timely services. In the fourth stage of the simulation...
Table 22 | GE response time of $D_4$.

| i  | 8  | 20 | 19 | 5  | 23 | 10 | 9  | 14 | 1  | 17 | 21 | 18 | 13 | 4  |
|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| D  | 720| 720| 720| 360| 360| 360| 360| 360| 360| 360| 360| 360| 360| 360|
| Tij| 12 | 95 | 19 | 18 | 79 | 36 | 28 | 7  | 9  | 21 | 44 | 9  | 41 | 8  |
| Tε | 60 | 60 | 70 | 30 | 40 | 40 | 50 | 40 | 80 | 20 | 80 | 40 | 50 | 30 |
| Tm | 25 | 37 | 45 | 9  | 52 | 37 | 21 | 38 | 39 | 37 | 4  | 12 | 58 | 8  |
| Ti | 817| 912| 854| 417| 531| 473| 459| 445| 488| 438| 488| 421| 509| 406|

Table 23 | OE response time of $D_4$.

| i  | 1  | 7  | 8  | 12 | 4  | 18 | 17 | 3  | 9  | 21 |
|----|----|----|----|----|----|----|----|----|----|----|
| D  | 1440| 720| 360| 360| 360| 360| 360| 360| 360| 360|
| Tij| 9   | 12 | 28 | 5  | 21 | 14 | 8  | 29 | 21 | 12 |
| Tε | 20  | 30 | 60 | 50 | 60 | 40 | 40 | 50 | 90 | 80 |
| Tm | 26  | 35 | 10 | 30 | 44 | 12 | 33 | 42 | 36 | 7  |
| Ti | 1495| 797| 458| 445| 485| 426| 441| 481| 507| 459|

Figure 1 | Comparison of efficiency.

Experiment, we had this situation, and our optimal strategy solved it well.

We found that even though the optimal point strategy was adjusted to meet the time constraints, the service rate of the adjusted system did not decrease much before the adjustment, still reaching 0.985, proving our model as a whole can significantly improve the service efficiency of the system.

Figures 2–4 refers to the incident probability under service rate adjustment. For each stage of the system with two different material scheduling strategies, the number of designated hospitals that the system needs to respond to is $\alpha_i$, the number of designated hospitals that present material requirements is $\beta_i$, and the number of designated hospitals that the final system finally responds to under the optimal strategy and general strategy is $\gamma_i$. In Figures 5 and 6, the changing trend of the number of patients with three different priorities. Taken together, the system reduces the number of designated hospitals that demand medical supplies in the next phase, and the total number of patients in each phase in three priority categories is significantly reduced. The reduction of the total number of patients means that the development trend of the epidemic has been well controlled, which indicates that our model has a good effect on improving the service rate of the system and controlling the epidemic.

Figure 2 | $\alpha_i$ Quantitative trend.

Figure 3 | Quantitative trend $\beta_i$.

Figure 4 | Quantitative trend $\gamma_i$. 
5. CONCLUSIONS

In recent years, large-scale public health emergencies such as infectious diseases have frequently occurred worldwide, seriously threatening people's lives and severely challenging the emergency management systems of all countries in the world. The timely supply of medical materials is essential to control the epidemic situation, among which emergency medical materials are the most important. Therefore, this paper proposes a Markov decision model for emergency medical material scheduling under public health emergencies such as infectious diseases, which discretizes the time of material scheduling continuously, describes the efficiency of medical material scheduling in a single period in detail, and finally obtains an optimality equation that maximizes the material efficiency of the whole system through iteration.

We applied the model to the scene of epidemic prevention and control in Wuhan and simulated the emergency medical material dispatching data of 24 designated hospitals in Wuhan under the condition of city closure management. According to the experimental data changes and results, our Markov decision model in the four stages dramatically improves the service rate in the event occurrence probability (transition rate). There are also many shortcomings in this paper. First, the designated hospitals in Wuhan are put forward in five batches, and the situations in other provinces and cities are given in batches in accordance with those in Wuhan. This paper does not consider the problems of different batches between such hospitals, and the default system initially has the nodes of the first three batches of hospitals. We did not give the basis for the priority evaluation of the response of designated hospitals in detail but simply considered the number, distance, materials, and other factors of three patient types. Our simulation experiment is only a simple numerical simulation, and the simulation time stage is also less, and the amount of data is not large enough; We did not discuss the different kinds of medical supplies that were dispatched. These shortcomings provide directions for our future research, such as combining deep learning methods in the simulation stage of the model to make the results more accurate. Combined with the problem of hospitals opening in batches, we consider adding a certain number of designated hospitals in different stages of efficiency iteration. In the application of the model, it is used to dispatch and distribute complex medical materials. In summary, this paper proposes the Markov decision model of emergency medical supplies under the public health emergencies of infectious diseases, which is suitable for the outbreak of public emergencies of infectious diseases, without considering the restrictions of personnel circulation and vehicle traffic in a closed environment. This method can make more efficient use of emergency medical supplies, improve the system's service rate, and effectively control the development of the epidemic.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.
AUTHORS’ CONTRIBUTIONS

Xiaojia Wang, Zhizhen Liang, Keyu Zhu contributed to the conception of the study; Zhizhen Liang performed simulation experiment; Xiaojia Wang contributed significantly to the model; Xiaojia Wang, Zhizhen Liang performed the data analyses and wrote the manuscript; Keyu Zhu helped perform the analysis with constructive discussions.

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