



Medical supplies scheduling in major public health emergencies

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ABSTRACT

In the early days of the COVID-19 pandemic in Wuhan, there was an unreasonable allocation between hospitals and a lack of timely transportation of medical supplies, which reduced the cure rate of infected cases. To solve the problem, this research proposes a method for scheduling medical supplies in major public health emergencies to develop a rapid and accurate supply scheme for medical materials, including the allocation of medical materials per vehicle to each hospital and the supply sequence per vehicle to each hospital. Specifically, this paper solves the following two sub-problems: (1) calculating the shortest transportation times and the corresponding routes from any distributing center(s) to any hospital(s); (2) calculating the medical supplies per vehicle transporting to each hospital. The method of solving sub-problem 1 is performed by multiple iterations, each of which calculates the shortest route from a distributing center, through one or more hospitals, and back to the distributing center. According to sub-problem 2, this research proposes a distribution model of medical supplies in major public health emergencies. A multiple dynamic programming algorithm which is a combination of some separated dynamic programming operations is proposed to solve this model. This algorithm also realizes the rapid updating of the scheme in the context of the changing number of vehicles. The first sub-problem can be solved in normal times, while the second one should be solved on the premise of obtaining the corresponding data after the occurrence of a major public health emergency. In the case study section, the whole method proposed in this research is employed in the medical supplies scheduling in the early stage of the COVID-19 outbreak in Wuhan, which proves the availability of the method. The main innovation of the method proposed in this research is that the problems can obtain the optimal solution while the time complexity is within an acceptable range.

1. Introduction

COVID-19 was discovered in Wuhan, China, in late 2019 and quickly spread around the world. In the early stage of the pandemic, there was a shortage of medical materials, as well as hospital beds and medical workers, which resulted in the situation that the hospitals were overwhelmed and the serious cross-infection between the patients. To maximize the utilization efficiency of the extremely limited medical supplies, the government designated only 5 hospitals to treat the infected cases. Several weeks later, with the arrival of medical supplies from all over the country or even the world, the number of designated hospitals had increased to over 50 in March 2020. The medical supplies gathered at the distributing centers, such as Wuhan airport and railway station, and then were

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transported from the distributing centers to the hospitals (Zhou et al., 2020; Li et al., 2020). However, although the quantity of the medical supplies had increased sharply, the medical system was in such chaos that the medical supplies were not well scheduled in the first few weeks. There were serious problems, such as unreasonable distribution and not timely transportation of the supplies, which caused needless deaths of the infected cases and were reported (or criticized) by the media (Zhu et al., 2020).

To improve the cure rate of patients in such major public health emergencies, medical supplies scheduling must achieve the goal of celerity and precision simultaneously. Consequently, the research question of this paper is how to schedule medical supplies in major public health emergencies within a short time, including the supply sequence of the vehicles to each hospital and the quantity of medical supplies on the vehicles that should be allocated to each hospital. The main contribution of this research is that it proposes the distribution and transportation models and algorithms of the medical supplies in major public health emergencies which can obtain the optimal solution with acceptable time complexity. The models and algorithms can be utilized to determine the optimal scheduling scheme of the medical supplies with the shortest transportation time which involves the allocation of medical supplies per vehicle to each hospital and the supply sequence per vehicle to each hospital.

2. Literature review

The recent research on emergency supplies mainly focuses on their preparation, supplement, scheduling, and transportation. Some researches aim to increase the operating efficiency of the whole system of emergency materials preparation, supplement, and scheduling (Kumar and Havey, 2013). For example, Liu and Xie (2015) proposed a workflow simulation system on emergency materials preparation and scheduling based on the Petri network by which the impact factors of emergency materials supply are figured out. By contrast, more scholars focus on one aspect of emergency materials preparation, supplement, or transportation. The preparation and supplement of the emergency materials are the important prerequisites of emergency rescue efforts (Liu et al., 2012). Many scholars have studied the optimal routine reserve of emergency materials for different types of emergencies. For example, (Ai et al., 2015) solved the location problem of the maritime emergency supplies reserve bases; Wu et al. (2015) proposed an emergency resources prediction and preparation model based on system dynamics; Liu et al. (2016) proposed an emergency material reserve optimization model in response to environmental accidents. In another aspect, there is also literature on the allocation and supplement of emergency materials after the occurrence of the disaster (Sheu, 2007). Liu and Xie (2016) proposed the emergency supplies requisition scheme and the negotiation principle of the government in disasters. In the response to major public health emergencies, Jacobson et al. (2012) proposed the model and algorithm to determine the medical supplies distribution considering the severity degree of the patients based on the sample-path methods and stochastic dynamic programming.

In the COVID-19 pandemic, the supply and demand disruptions significantly affect the supply chain network, which can also reduce the efficiency of medical materials supply in response to the pandemic (Li et al., 2021; Aldrighetti et al., 2021). In this context, Nikolopoulos et al. (2021) proposed an approach forecasting the excess demand for products and services during the COVID-19 pandemic based on statistical, epidemiological, machine- and deep-learning models. Govindan et al. (2020) developed a decision support system for demand management in healthcare supply chains in the pandemic. Naderi et al. (2021) proposed a generalized operating room planning and scheduling method in the context of limited resources. Mehrotra et al. (2020) proposed a stochastic optimization model for allocating and sharing a critical resource in the case of a pandemic. Corominas (2021) proposed a permanent reserve model to immediately meet the demand for equipment at the beginning and throughout a pandemic. Additionally, the traffic situation in the COVID-19 pandemic is significantly different from normal situations due to the strict control by the government (Chen et al., 2020). Therefore, optimizing the medical supplies transportation scheme in such major public health emergencies is a new research question. However, the research on medical materials allocation and transportation in major public health emergencies, such as COVID-19, is insufficient.

The scheduling of emergency materials is essentially a vehicle routing problem (VRP). The heuristic algorithms are commonly utilized to solve this type of problem, including the ant colony algorithm (Bullnheimer et al., 1999), tabu search algorithm (Gendreau et al., 1999), genetic algorithm (Ardjmand et al., 2015), symbiotic organism search (Yu et al., 2017), etc. In the aspect of emergency materials scheduling, Zhang et al. (2011) established an adaptively mutate genetic algorithm to solve the problem. Liu and Xie (2017) established an emergency materials scheduling model and its solution method based on the dynamic programming and ant colony algorithm considering the continual alteration of material demand and vehicle amount. However, the algorithm complexity proposed by the research is high. While solving the problems with many demand areas and vehicles, the application of heuristic algorithms may save time but can only obtain satisfactory solutions but not the optimal solution. Therefore, this research aims to propose a method to obtain the optimal medical supplies scheduling scheme in major public health emergencies.

One of the most important sub-problem in emergency supplies scheduling is the shortest path problem. The Dijkstra algorithm and the improved algorithms based on it are important methods to solve the problem (Wang et al., 2009; Ciesielski et al., 2018). Yuan and Wang (2009) proposed an improved Dijkstra algorithm to calculate the shortest transportation time of emergency supplies considering the chaos, panic, and congestion in the disaster. In the pre-planning phase, the shortest transportation routes are calculated and can be invoked in an emergency. Wang et al. (2020) proposed a two-level method based on the Dijkstra algorithm and ant colony algorithm and established an emergency material scheduling system based on the Internet of Things. However, the Dijkstra algorithm has a high time complexity and is only suitable for solving complex problems in non-urgent cases (Kou et al., 2020). Compared with the literature above, we improve the Dijkstra algorithm in this research to calculate the shortest route from a distributing center, through one or more hospitals, and back to the distributing center. This method can be employed before the occurrence of a major public health emergency.

The dynamic programming approach can be utilized to obtain the optimal solution to the vehicle routing problem (Baldacci and

Mingozi, 2009; Shapiro, 2017). Dynamic programming is essentially a modeling idea that divides the complex problem into several simple ones to solve successively (Bertsekas, 2017; Ben Ticha et al., 2019). Novoa and Storer (2009) solved the single-vehicle routing problem with stochastic demands by the integrated application of approximate dynamic programming and Monte Carlo cost-to-go estimation. Munari et al. (2019) employed the dynamic programming approach to solve the robust vehicle routing problem with time windows. Tikani and Setak (2019) proposed a restricted dynamic programming algorithm to solve the emergency materials scheduling problem. While it is unrestricted, the algorithm can reach an optimal solution. Otherwise, a satisfactory solution is obtained by a heuristic algorithm. By comparison, we propose a multiple dynamic programming algorithm in this research that can simultaneously work out optimal solutions and control the calculation time based on the improved Dijkstra algorithm.

The remainder of this paper is organized as follows. Section 3 defines the research problem. Section 4 proposes the models and their solutions that obtain the optimal transportation routes of medical supplies and the optimal distribution scheme of medical supplies. Section 5 is the case study on the medical supplies scheduling in Wuhan in the COVID-19 pandemic.

3. Problem definition

After a major public health emergency occurs, medical supplies are first gathered at the distributing centers, such as airports and railway stations, and then transported from the distributing centers to the medical centers (hospitals). This research proposes several models and algorithms which are utilized to obtain the medical supplies scheduling scheme from the distributing centers to the hospitals in major public health emergencies. This scheme involves the following items: the allocation of medical supplies per vehicle to each hospital and the supply sequence per vehicle to each hospital. The information which should be available to the decision-makers in prior to performing the models and algorithms includes: the total amount of medical supplies in each distributing center, the medical materials demand of each hospital, the maximum capacity of each vehicle, and the minimum transportation time between each two distributing centers or hospitals.

Unlike other major disasters, such as earthquakes and tsunamis, the distributing centers, medical centers, and the routes among them would not be destroyed in major public health emergencies. Therefore, if the distributing centers and medical centers in a country or region in major public health emergencies are determined previously in the emergency plan, then the expected transportation time and the path between each two distributing centers or hospitals can be calculated in advance based on the GIS. Consequently, the complex vehicle routing problem of medical supplies scheduling in major public health emergencies can be divided into the following two sub-problems to solve.

Sub-problem 1: Calculating the shortest transportation times and the corresponding routes from any distributing center(s) to any hospital(s). The data needed to solve this problem are the expected transportation time and path between each two distributing centers or hospitals. This problem can be solved in advance rather than in an emergency scenario. The calculation results are stored in the database for invocation while solving sub-problem 2.

Sub-problem 2: Calculating the quantity of medical supplies per vehicle transporting to each hospital. The data needed to solve the problem include the total amount of medical supplies at each distributing center, the medical materials demand of each hospital, and the maximum capacity of each transport vehicle. Therefore, this problem should be solved on the premise of obtaining the data above after the occurrence of a major public health emergency.

The following section of this paper will give models and solutions to the two sub-problems.

4. Modeling and solution

4.1. Medical supplies optimal transportation routes in major public health emergencies

This section solves the “Sub-problem 1” introduced previously that calculating the optimal transportation routes of medical supplies from any distributing center(s) to any hospital(s). Specifically, the shortest transportation time between each two distributing centers or hospitals is collected first in which the loading and unloading time is included. A vehicle starts from a distributing center, supplies several hospitals (hereinafter referred to as the “target hospitals”) in sequence, and then returns to the distributing center. Therefore, this research proposes the method to obtain the supply sequence of the target hospitals with the shortest total transportation time (hereinafter referred to as the “optimal transportation route”).

A network is constructed in which a node represents a distributing center or hospital, an arc denotes the path between every two nodes, and the weight of the arc is the shortest time that a vehicle passes through the path. Since all the hospitals are connected to the outside world by roads, the network is connected. Then, the key to solving sub-problem 1 is to solve the shortest route problem (refers to the shortest time in this research) that a vehicle departs from the starting point, passes through several intermediate nodes, and then returns to the starting point in the network. The calculation of this method is performed by multiple iterations, each of which calculates the shortest route from a specific distributing center, through the specific hospital(s), and back to the distributing center (hereinafter referred to as the “center-hospital-center combination”). In one iteration, all the target hospitals should be the intermediate nodes, but an intermediate node may not always be the target hospital. Solving sub-problem 1 is not subject to time constraints strictly because the problem need not necessarily be solved in the scenario of a major public health emergency. Therefore, this research proposes a method to obtain the exact optimal solution to sub-problem 1 by improving the Dijkstra algorithm. The notations of this method are as follows: N - Total number of hospitals; n - Quantity of target hospitals; M - Number of distributing centers; H_i - Hospital i ; D_i - Distributing center i .

The key steps of the method are as follows.

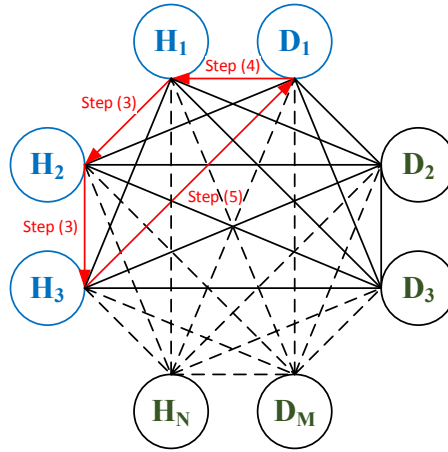


Fig. 1. Calculation procedure on a schematic network.

- (1) Construct the matrix CP of target hospital selection. The elementary events of target hospital selection are stored in the matrix. Each column represents the possible elementary events that selecting n hospitals from a total of N hospitals. Then, the number of columns in CP is $\sum_{n=1}^N C_N^n$. Each row represents the elementary events that a hospital is selected as a target hospital or not. Then, the number of rows in CP is N . The elements of the matrix are either 0 (indicating that the corresponding hospital is not selected as a target hospital) or 1 (indicating that the corresponding hospital is selected as a target hospital). The matrix CP is represented as follows:

$$\begin{array}{c}
 H_1 \\
 H_2 \\
 H_3 \\
 \vdots \\
 H_{N-2} \\
 H_{N-1} \\
 H_N
 \end{array}
 \left[
 \begin{array}{cccccc}
 1 & 0 & 1 & 0 & 1 \\
 0 & 0 & 1 & 0 & 1 \\
 0 & 0 & 0 & 0 & 1 \\
 \vdots & \ddots & \vdots & \vdots & \vdots \\
 0 & 0 & 0 & 0 & 1 \\
 0 & 0 & 0 & 1 & 1 \\
 0 & 1 & 0 & 1 & 1
 \end{array}
 \right]$$

1 Target Hospital
2 Target Hospitals
 n Target Hospitals

in which the first column represents the elementary event that selecting only hospital H_1 , while the last column represents that selecting all the N hospitals.

- (2) Build the target hospital sequence set HP . The set includes the full permutation of the selected target hospitals in which each permutation (hereinafter referred to as the “target hospital sequence”) is regarded as an element in this set. Every column of CP has one Corresponding HP . For example, according to the column $[1, 1, 1, 0, \dots, 0]^T$ of CP , the Corresponding HP has 6 elements which are “ H_1, H_2, H_3 ”, “ H_2, H_1, H_3 ”, “ H_1, H_3, H_2 ”, “ H_3, H_1, H_2 ”, “ H_2, H_3, H_1 ”, and “ H_3, H_2, H_1 ”. The number of elements in HP is $n!$. Consequently, in sub-problem 1, the total amount of the target hospital sequences is $\sum_{n=1}^N A_N^n$.
- (3) Calculate the shortest route in the target hospital sequence. For each target hospital sequence, the shortest route of vehicles passing through all the target hospitals is calculated. In this process, the Dijkstra algorithm is utilized to solve the shortest route between every two adjacent target hospitals.
- (4) Calculate the shortest route from the starting point to the target hospital sequence. Specifically, the Dijkstra algorithm is employed to calculate the shortest route from each distributing center to the first target hospital in the target hospital sequence.
- (5) Calculate the shortest route from the target hospital sequence to the endpoint. Specifically, the Dijkstra algorithm is used to calculate the shortest route from the last target hospital in the target hospital sequence to each distributing center.

Fig. 1 is a schematic network of the hospitals and distributing centers. According to the first element “ H_1, H_2, H_3 ” of HP , the calculation procedure of steps (3), (4), and (5) is shown by the colored parts in Fig. 1.

- (6) Determine the optimal transportation route for the center-hospital combination. Specifically, for every distributing center, the shortest route of each target hospital sequence can be obtained by connecting, in turn, the shortest routes in steps (4), (3), and (5). Multiple shortest routes can be obtained for a center-hospital combination. Then, the route with the shortest transportation time in the shortest routes is the optimal transportation route of the center-hospital combination.

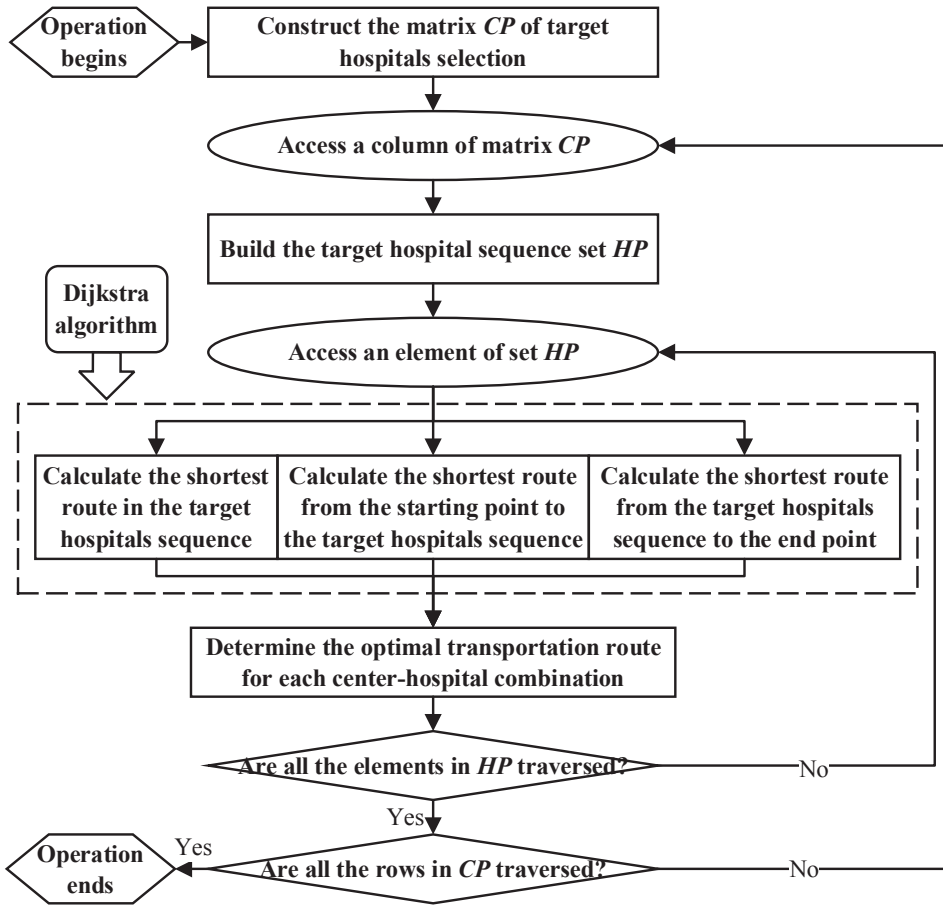


Fig. 2. Solution process of sub-problem 1.

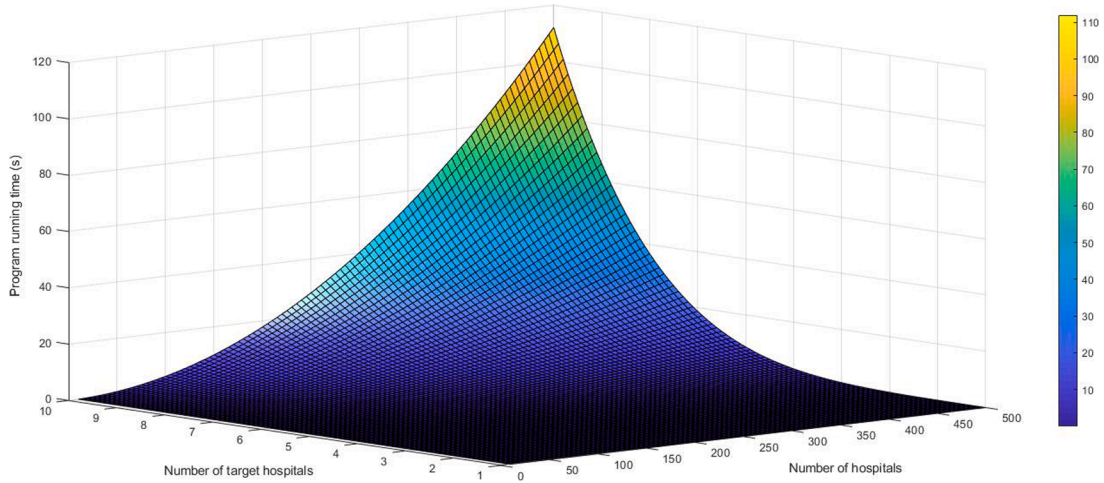


Fig. 3. Running time of solving Sub-problem 1 in different data sizes.

The solution process of sub-problem 1 is shown in Fig. 2.

The running time of the algorithm program of sub-problem 1 is determined only by the total amount of nodes in the network (namely the total number of hospitals) and the maximum number of intermediate nodes that must pass through (hereinafter referred to

as the “number of target hospitals”). The time complexity of this algorithm is $O(N^2 \times n!)$. Therefore, compared with the increase in the total number of hospitals, the increase in the number of target hospitals can prolong the running time of the algorithm more significantly. By testing in a microcomputer (CPU: Intel Core i5-4210H, RAM: 4 GB), the average running time of the algorithm while the total number of hospitals is within the range of [10, 500] and the number of target hospitals is within the range of [1, 10] is demonstrated in Fig. 3. It can be seen from this figure that the running time of the algorithm program is only 112 s while the total number of hospitals is 500 and the number of target hospitals is 10. Consequently, the time complexity of this algorithm meets the practical requirements.

4.2. Medical supplies optimal distribution scheme in major public health emergencies

This section proposes the distribution model and algorithm of medical supplies in major public health emergencies to solve the “Sub-problem 2” introduced previously which is the allocation of medical supplies among the hospitals and the vehicles. In practice, if different kinds of medical supplies need to be transported in a certain proportion, then the whole after collocation is regarded as a new kind of supplies that can be analyzed in the model. Consequently, this section focuses on the distribution of the same category of medical supplies. Let the amount of the medical supplies be a non-negative integer. There are one or more distributing centers, each of which has one or more vehicles that can be used to transport the medical supplies. A vehicle belonging to a distributing center set out from the center to supply medical materials to the hospitals and then return to the center. Additionally, one transportation round of a vehicle refers that it sets out from the distributing center to supply medical materials to the hospitals and then return to the distributing center. Due to the continuous flow of medical supplies from all over the country and the world at the distributing centers, the total supply of medical materials is uncertain. Therefore, considering the timely loading of newly arrived medical materials and the reduction of transportation costs, we assume that the vehicles should be loaded as fully as possible. Considering the urgency of hospital demand for medical supplies decreases with the increase of supply quantity and the humanitarian factors, we suppose that the medical materials on a vehicle should be supplied to as few hospitals as possible in one transportation round. We continue to use the notations in the previous section in this distribution model and propose the other notations utilized in this model as follows: U_i - Total medical materials quantity in distributing center i ; Q_{ij} Carrying capacity of vehicle j belonging to distributing center i ; R_h - Demand for medical supplies of hospital h ; x_{ijkh} - Quantity of medical materials that vehicle j belonging to distributing center i supplies hospital h in round k ; T_{ijk} - Transportation time needed by vehicle j belonging to distributing center i in round k ; V - Total number of vehicles. To represent whether vehicle j belonging to distributing center i supplies hospital h in round k , we use Boolean y_{jh} which is

$$\begin{cases} y_{jh} = 1, x_{ijkh} > 0 \\ y_{jh} = 0, x_{ijkh} = 0 \end{cases}.$$

Therefore, whether the vehicle j belonging to distributing center i in round k supplies each hospital can be represented as $Y_{ijk} = [y_{1j}, y_{2j}, \dots, y_{Nj}]$. If Y_{ijk} matches a column of the target hospital selection matrix CP given previously, the corresponding transportation time and the route can be obtained. This transportation time is denoted as $T_{ijk}(x_{ijk1}, x_{ijk2}, \dots)$. Consequently, the transportation time needed by vehicle j belonging to distributing center i is $\sum_k T_{ijk}(x_{ijk1}, x_{ijk2}, \dots)$.

The total time required to complete the transportation of all medical supplies is the maximum transportation time for all the vehicles. Consequently, the objective is to minimize the maximum transportation time. Moreover, the quantity of medical materials that vehicle j belonging to distributing center i supplies in each transportation round should not exceed the carrying capacity of this vehicle. The quantity of medical materials supplied by distributing center i does not exceed its total quantity of medical materials.

If the total supply of medical materials is greater or equal to the total demand, then the actual quantity of supply should be the demand of the hospitals. Meanwhile, the surplus medical supplies should be stored at the distributing center in case of emergency extra demand scenarios. At this point, the quantity of medical supplies obtained by hospital h is equal to its demand. In this case, the distribution model is proposed as follows:

$$\begin{aligned} \min T &= \max_i [\max_j \sum_k T_{ijk}(x_{ijk1}, x_{ijk2}, \dots)] \\ \text{s.t.} \quad &\begin{cases} \sum_h x_{ijkh} \leq Q_{ij} \\ \sum_j \sum_k \sum_h x_{ijkh} \leq U_i \\ \sum_i \sum_j \sum_k x_{ijkh} = R_h \\ x_{ijkh}, Q_{ij}, U_i, R_h \geq 0 \end{cases} \\ &i = 1, 2, \dots; j = 1, 2, \dots; k = 1, 2, \dots; h = 1, 2, \dots \end{aligned}$$

If the total supply of medical materials is less than the total demand, then the actual supply of medical materials for hospital h is set as $\sum_i \frac{U_i}{R_h} \times R_h$ based on the fairness principle. In this case, the distribution model is proposed as follows:

$$\begin{aligned}
\min T &= \max_i [\max_j \sum_k T_{ijk}(x_{ijk1}, x_{ijk2}, \dots)] \\
\text{s.t.} &\left\{ \begin{aligned} &\sum_h x_{ijkh} \leq Q_{ij} \\ &\sum_j \sum_k \sum_h x_{ijkh} \leq U_i \\ &\sum_i \sum_j \sum_k x_{ijkh} = \frac{\sum_i U_i}{\sum_h R_h} \times R_h \\ &x_{ijkh}, Q_{ij}, U_i, R_h \geq 0 \\ &i = 1, 2, \dots; j = 1, 2, \dots; k = 1, 2, \dots; h = 1, 2, \dots \end{aligned} \right.
\end{aligned}$$

We propose a “multiple dynamic programming algorithm” to solve this model. This algorithm is a combination of some separated dynamic programming operations that is utilized to calculate the optimal solution under the reasonable hypotheses given previously in this section. The process of this algorithm is divided into several phases, while one transportation round of a vehicle is regarded as one phase. Specifically, “phase $i.j.k$ ” represents the transportation of vehicle j belonging to distributing center i in round k . The notations in this algorithm are as follows: n_{ijk} - Number of hospitals that need to supply (or target hospital) in phase $i.j.k$; u_{ijk}^d - Quantity of medical materials that have already been supplied from distributing center d ; r_{ijk}^h - Quantity of medical materials that have already been acquired by hospital h ; t_{ijk}^{ab} - Transport time of vehicle b belonging to distributing center a from the end of phase $i.j.k$ to the end of the final phase; S_{ijk} - Quantity of medical materials that have already been supplied from each distributing center and medical materials that have already been acquired by each hospital at the beginning of phase $i.j.k$; X_{ijk} - Quantity of medical materials supplied to each hospital by vehicle j belonging to distributing center i in round k at the beginning of phase $i.j.k$; $T(S'_{ijk})$ - Minimum total transport time from the end of phase $i.j.k$ to the end of the final phase; $t(S_{ijk}, X_{ijk})$ - Expected transport time of vehicle j belonging to distributing center i in round k while decision X_{ijk} is implemented in the state of S_{ijk} ; $V(S_{ijk}, X_{ijk})$ - Total transport time from the beginning of phase $i.j.k$ to the end of the final phase while decision X_{ijk} is implemented in the state of S_{ijk} ; $T(S_{ijk})$ - Minimum value of $V(S_{ijk}, X_{ijk})$ in phase $i.j.k$.

In the dynamic programming operations, the state variable is S_{ijk} which is defined as

$$S_{ijk} = (u_{ijk}^1, u_{ijk}^2, \dots, r_{ijk}^1, r_{ijk}^2, \dots).$$

The decision variable is X_{ijk} which is defined as

$$X_{ijk} = (x_{ijk1}, x_{ijk2}, \dots).$$

Additionally, we can easily obtain $\sum_h x_{ijkh} \leq U_i - u_{ijk}^i$, $\sum_h x_{ijkh} \leq Q_{ij}$, and $x_{ijkh} \leq R_h - r_{ijk}^h$.

In phase $i.j.k$, the amount of the medical materials that are supplied from distributing center i is $\sum_h x_{ijkh}$, while medical materials that are acquired by hospital $1, 2, \dots$ are $x_{ijk1}, x_{ijk2}, \dots$, respectively. Therefore, the state at the end of the phase is

$$S'_{ijk} = (u_{ijk}^1, \dots, u_{ijk}^i + \sum_h x_{ijkh}, \dots, r_{ijk}^1 + x_{ijk1}, r_{ijk}^2 + x_{ijk2}, \dots).$$

$T(S'_{ijk})$ can be considered as the longest total transport time of the vehicles from the end of phase $i.j.k$ to the end of the final phase, that is,

$$T(S'_{ijk}) = \max(t_{ijk}^{11}, t_{ijk}^{12}, \dots, t_{ijk}^{21}, t_{ijk}^{22}, \dots).$$

Then, the phase indicator in the dynamic programming operations is $t(S_{ijk}, X_{ijk})$ which can be obtained based on the calculation results of sub-problem 1. Therefore, the transport time of vehicle j from the beginning of phase $i.j.k$ to the end of the final phase is $t_{ijk}^{ij} + t(S_{ijk}, X_{ijk})$.

The process indicator in the dynamic programming operations is $V(S_{ijk}, X_{ijk})$ which is defined as

$$V(S_{ijk}, X_{ijk}) = \max\{T(S'_{ijk}), t_{ijk}^{ij} + t(S_{ijk}, X_{ijk})\}.$$

Thus, in phase $i.j.k$, we should find out the optimal decision X_{ijk}^* implemented in the state of S_{ijk} which minimizes the $V(S_{ijk}, X_{ijk})$. This shortest time, $T(S_{ijk})$, is the optimal indicator in the dynamic programming operations which is defined as

$$T(S_{ijk}) = \min_{X_{ijk}} \{\max\{T(S'_{ijk}), t_{ijk}^{ij} + t(S_{ijk}, X_{ijk})\}\}.$$

The initial state of the whole algorithm process is $(0, 0, \dots, 0, 0, \dots)$, while the final state is $(U_1, U_2, \dots, R_1, R_2, \dots)$. We make a backward deduction from the final state to the initial state. Additionally, if phase $i'.j'.k'$ is the final phase, then the boundary condition of the dynamic programming algorithm above is $T(S'_{i'j'k'}) = 0$.

While determining the decisions that can be chosen, the first consideration is to supply all the medical materials on the vehicle to only one hospital; otherwise, consider supplying only two hospitals, and so on. During the transportation process, the number of transportation rounds of each vehicle would be different. There may be multiple possible cases for a phase, each of which considers the

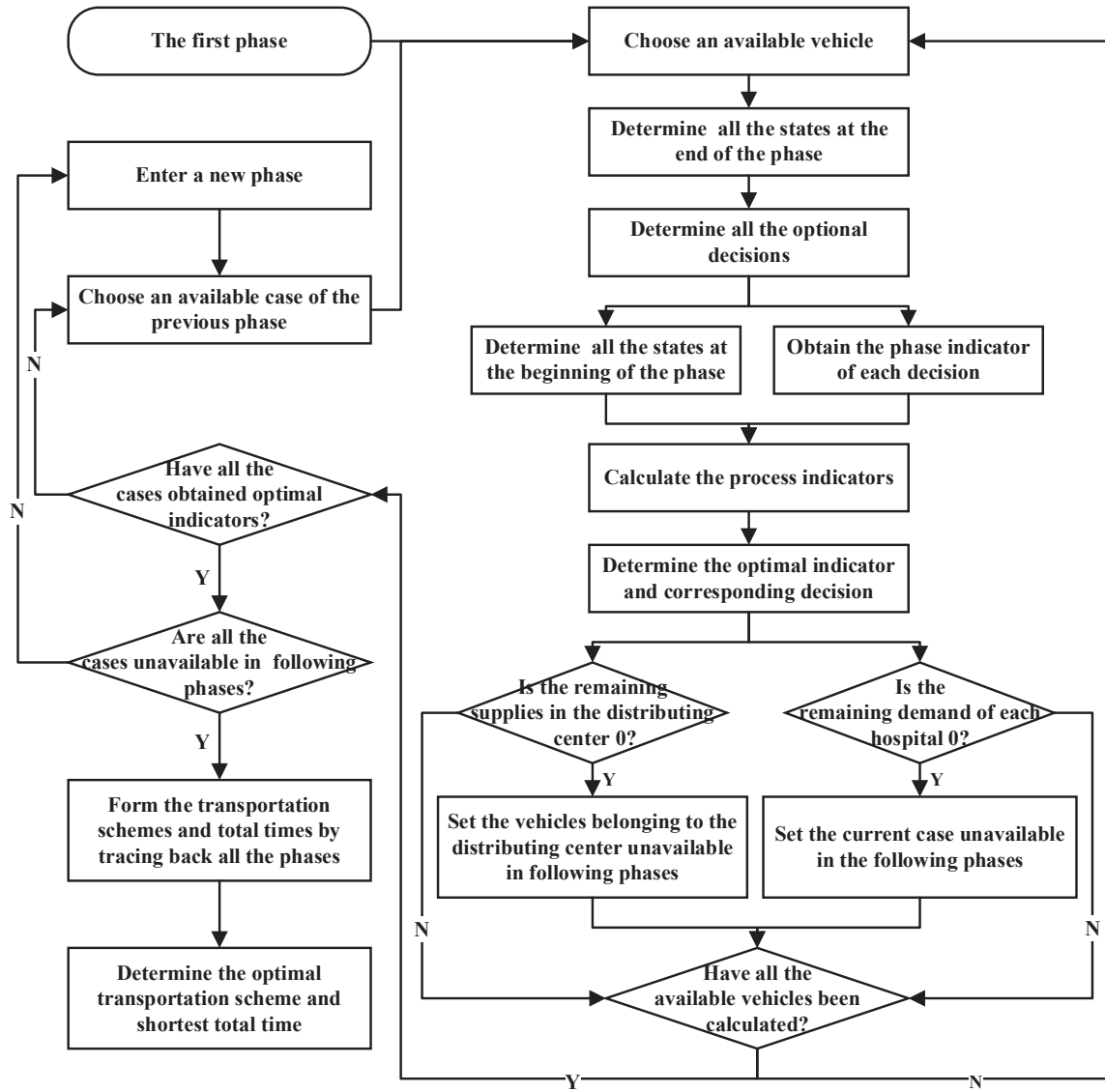


Fig. 4. Multiple dynamic programming algorithm process.

transportation of a vehicle. Each case for the former phase is the premise of the corresponding case in the latter phase. After the calculation of a case, if the remaining supplies in the distributing centers is not 0, then each vehicle belonging to this distributing center should be considered in the next phase; otherwise, the vehicles belong to the distributing center are set “unavailable”, that is, they are not considered in any of the cases for the following phases. If the demand of each hospital is 0, then the current case is set “unavailable”, that is, each case in the following phases is not premised on the current case. Therefore, the permutation and combination of the probable cases for each phase form many single dynamic programming problems. By calculating the total time of each problem one by one, the shortest total time which is also the optimal solution can be obtained. In summary, the process of the multiple dynamic programming algorithm is shown in Fig. 4. Additionally, there is only one case for the first phase which has only one end state, namely, the final state. All the vehicles on standby at the distributing centers are available in this phase.

In the practical process of medical materials transportation in major public health emergencies, the number of vehicles that are used to transport the medical materials may change over time. In this scenario, the multiple dynamic programming algorithm proposed in this research allows considering the new information in the corresponding phases in the calculating process and accomplishing the subsequent process without a complete recalculation. Specifically, the condition that vehicle j belonging to distributing center i joins the transportation effort of medical materials after time t_{ij} can be regarded as that the vehicle has the first round of transportation of which the time consuming is t_{ij} . Consequently, the vehicle can be added to the operation process from the second round.

The running time of the multiple dynamic programming algorithm program is determined by the total number of vehicles and the

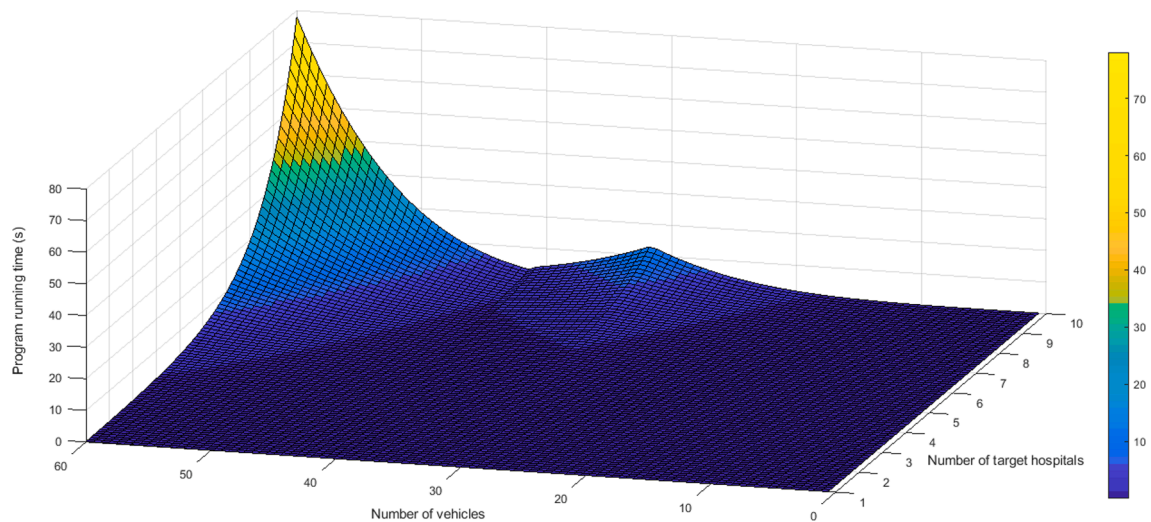


Fig. 5. Running time of solving Sub-problem 2 in different data sizes.

Table 1

Shortest transportation times between each two places.

	●	①	②	③	④	⑤
○	40	19	27	∞	39	40
①	25	0	14	37	27	26
②	22	14	0	32	15	16
③	23	37	32	0	32	41
④	36	27	15	32	0	15
⑤	∞	26	16	41	15	0

maximum number of hospitals that need to supply in each phase. The time complexity of this algorithm is $O(2^{\max\{n_{ijk}\}} V^4)$. Therefore, compared with the increase in the number of vehicles, the increase in the maximum number of hospitals that need to supply in each phase would lengthen the running time of the algorithm more significantly. By testing on the microcomputer in the previous section, the average running time of the algorithm program while the total number of vehicles is within the range of [1, 60] and the number of target hospitals in each phase is within the range of [1, 10] is demonstrated in Fig. 5.

As can be seen in Fig. 5, the running time of the program increases with the number of target hospitals. By contrast, with the increase of the number of vehicles, the running time first increases slowly, then decreases slowly, and finally increases rapidly. The reason is that the increase in the number of vehicles contributes to the fast outbound transportation of the medical supplies, which may reduce the iteration times of the calculation program. In most cases, the running time of the program is within 80 s. Compared with the other similar materials scheduling algorithms (Chang et al., 2014; Wang et al., 2014), the time complexity of this algorithm is acceptable. Practically, it meets the requirement of emergency response to major public health emergencies.

5. Case study and managerial insights

5.1. Case overview

In the early stage of the COVID-19 outbreak in Wuhan, many medical supplies were gathered from all over the country and the world at the Wuhan airport (distributing center 1, hereinafter referred to as “○”) and Wuhan railway station (distributing center 2, hereinafter referred to as “●”). Meanwhile, the government designated five hospitals to treat critically ill patients infected, including Wuhan Jinyintan Hospital (hereinafter referred to as “①”), Wuhan Pulmonary Hospital (hereinafter referred to as “②”), Renmin Hospital of Wuhan University (hereinafter referred to as “③”), Wuhan Union Hospital (hereinafter referred to as “④”), Wuhan Tongji Hospital (hereinafter referred to as “⑤”). The shortest transportation times between each two of these hospitals and the airport and railway station that are shown in Table 1 can be obtained by GIS (such as AMAP) (if there is no road directly connecting the two places, then it is expressed as “∞”).

There were supposed to be 110 and 100 tons of medical materials in the Wuhan airport and Wuhan railway station, respectively. There were 2 vehicles in Wuhan airport which can be used in medical materials transportation, in which one vehicle with the carrying capacity of 30 tons (hereinafter referred to as “V1”) was on standby at the airport while the other one with the carrying capacity of 20 tons (hereinafter referred to as “V2”) was able to join the transportation effort in 60 min. The medical materials demand of hospital ①,

Table 2
Matrix *CP* in this case.

	I					II					III										IV					V					
①	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	1	1	1	1	0	1
②	0	1	0	0	0	1	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	1	1	1	0	1	1	1	0	1	1
③	0	0	1	0	0	0	1	0	0	1	0	0	1	1	0	1	0	0	1	1	0	1	1	0	1	1	1	0	1	1	1
④	0	0	0	1	0	0	0	1	0	0	1	0	1	0	1	0	1	0	1	1	1	1	0	1	1	1	0	1	1	1	1
⑤	0	0	0	0	1	0	0	0	1	0	0	1	0	1	1	0	0	1	0	1	1	1	0	1	1	1	0	1	1	1	1

Table 3
Optimal transportation routes and corresponding transportation times.

No.	Target hospitals combinations	Airport-hospital		Station-hospital	
		Optimal Routes	Time (min)	Optimal Routes	Time (min)
1	1 0 0 0 0	○①○	38	●①●	50
2	0 1 0 0 0	○②○	54	●②●	44
3	0 0 1 0 0	○①③①○	112	●③●	46
4	0 0 0 1 0	○④○	78	●④●	72
5	0 0 0 0 1	○⑤○	80	●②⑤②●	76
6	1 1 0 0 0	○①②○	60	●①②●	61
7	1 0 1 0 0	○①③①○	112	●①③●	85
8	1 0 0 1 0	○①④○	85	●①④●	88
9	1 0 0 0 1	○①⑤○	85	●①⑤②●	89
10	0 1 1 0 0	○②③①○	115	●②③●	77
11	0 1 0 1 0	○②④○	81	●②④●	73
12	0 1 0 0 1	○②⑤○	83	●②⑤②●	76
13	0 0 1 1 0	○①③④○	127	●③④●	91
14	0 0 1 0 1	○①③⑤○	137	●③⑤②●	102
15	0 0 0 1 1	○④⑤○	94	●④⑤②●	89
16	1 1 1 0 0	○②③①○	115	●①②③●	94
17	1 1 0 1 0	○①②④○	87	●①②④●	90
18	1 1 0 0 1	○①②⑤○	89	●①⑤②●	89
19	1 0 1 1 0	○①③④○	127	●③④①●	127
20	1 0 1 0 1	○①③⑤○	137	●③⑤①●	115
21	1 0 0 1 1	○①④⑤○	101	●①⑤④●	102
22	0 1 1 1 0	○②③④○	130	●②④③●	92
23	0 1 1 0 1	○②③⑤○	140	●②⑤③●	102
24	0 1 0 1 1	○④⑤②○	97	●②⑤④●	89
25	0 0 1 1 1	○①③④⑤○	143	●③④⑤②●	108
26	1 1 1 1 0	○①③④②○	130	●①②④③●	109
27	1 1 1 0 1	○①③⑤②○	140	●①②⑤③●	119
28	1 1 0 1 1	○④⑤②①○	103	●①⑤④②●	103
29	1 0 1 1 1	○①③④⑤○	143	●①⑤④③●	121
30	0 1 1 1 1	○②③④⑤○	146	●②⑤④③●	108
31	1 1 1 1 1	○②③④⑤①○	151	●③④⑤②①●	125

②, ③, ④, and ⑤ was 120, 100, 80, 60, and 60 tons, respectively. The approach proposed in this paper is applied to calculate the optimal scheduling scheme for medical supplies in this section. Specifically, the optimal transportation route of medical supplies is first calculated; then, the optimal distribution scheme of the medical supplies is obtained.

5.2. Medical supplies optimal transportation routes in Wuhan COVID-19 pandemic

This section calculates the optimal transportation routes of medical supplies in the COVID-19 pandemic in Wuhan based on the method proposed in this research. The work can be completed in normal time and the results can be stored for invocation.

- (1) Construct the matrix CP of target hospital selection. Since the total number N of hospitals is 5, CP has 31 columns and 5 rows. Moreover, all the target hospital combinations can be divided into five categories. Category I, II, III, IV, and V represent the situations that there are 1, 2, 3, 4, and 5 target hospitals, respectively. The matrix is shown in Table 2. For example, the last column of Table 2 indicates that all hospitals are selected as the target hospitals.
- (2) Access cyclically each column of the matrix CP and construct the target hospital sequence set HP one by one. Take the 10th column in category III as an example, namely, choose hospital ③, ④, and ⑤ as the target hospitals. Therefore, the number of elements in the set HP is 6, and we obtain

$$HP = \{(3)(4)(5), (3)(5)(4), (4)(3)(5), (4)(5)(3), (5)(3)(4), (5)(4)(3)\}$$

- (3) Visit every element in the set HP and calculate the shortest route in the target hospital sequence, the shortest route from the starting point to the target hospital sequence, and the shortest route from the target hospital sequence to the endpoint, and then determine the optimal transportation route for the center-hospital combination. Take the HP given in step (2) as an example. For the first target hospital sequence, namely, the element “③④⑤” in HP , the shortest transportation time and the corresponding route is calculated based on the Dijkstra algorithm which is 47 min and ③④⑤, respectively. The shortest transportation time from Wuhan airport or Wuhan railway station to the target hospital sequence is 56 min (the route is ○①③, which means the vehicle must pass the hospital ①) or 23 min (the route is ●③), respectively. The shortest transportation time from the target hospital sequence to Wuhan airport or railway station is 40 min (the route is ⑤○) or 38 min (the route is ⑤②●, which means the vehicle must pass the hospital ②), respectively. For each target hospital sequence in HP , if the distributing center is the Wuhan airport, then the shortest transportation time of this target hospital sequence is 143 min and the corresponding route is

Table 4

Calculation results of each variable in the first phase.

Case	State at the beginning	Decision	State at the end	Phase indicator	Process indicator	Optimal indicator	Optimal decision
1	80,100;30,50,40,30,30	30,0,0,0,0	110,100;60,50,40,30,30	38	38	38	30,0,0,0,0
	80,100;60,20,40,30,30	0,30,0,0,0	110,100;60,50,40,30,30	54	54	54	0,30,0,0,0
	80,100;60,50,10,30,30	0,0,30,0,0	110,100;60,50,40,30,30	112	112	112	0,0,30,0,0
	80,100;60,50,40,0,30	0,0,0,30,0	110,100;60,50,40,30,30	78	78	78	0,0,0,30,0
	80,100;60,50,40,30,0	0,0,0,0,30	110,100;60,50,40,30,30	80	80	80	0,0,0,0,30
2	110,75;35,50,40,30,30	25,0,0,0,0	110,100;60,50,40,30,30	38	38	38	25,0,0,0,0
	110,75;60,25,40,30,30	0,25,0,0,0	110,100;60,50,40,30,30	54	54	54	0,25,0,0,0
	110,75;60,50,15,30,30	0,0,25,0,0	110,100;60,50,40,30,30	112	112	112	0,0,25,0,0
	110,75;60,50,40,5,30	0,0,0,25,0	110,100;60,50,40,30,30	78	78	78	0,0,0,25,0
	110,75;60,50,40,30,5	0,0,0,0,25	110,100;60,50,40,30,30	80	80	80	0,0,0,0,25

○①③④⑤○; if the distributing center is the Wuhan railway station, then the shortest transportation time of this target hospital sequence is 108 min and the corresponding route is ●③④⑤②●. Therefore, by the analysis of each element in *HP*, we obtain that the optimal transportation route for the “airport-hospital” combination and the “station-hospital” combination is ○①③④⑤○ and ●③④⑤②●, respectively.

- (4) Return to step (2) until all the columns in matrix *CP* have been accessed. Finally, the optimal transportation routes and the corresponding transportation time of all “airport-hospital” combinations and “station-hospital” combinations are obtained. Additionally, the transportation time of a route in the forward direction and reverse direction is equal. For example, the transportation time of routes ○①②○ and ○②①○ are the same. Consequently, we only list one route representing both the forward direction and reverse direction as the result which is shown in Table 3.

Table 3 includes the optimal transportation routes for the vehicles and the corresponding transportation times in all cases. These data are the basis for formulating the optimal distribution scheme for medical supplies.

5.3. Medical supplies optimal distribution scheme in Wuhan COVID-19 pandemic

This section calculates the optimal distributing scheme of medical supplies in the COVID-19 pandemic in Wuhan based on the method proposed in this research. The work should be completed after the occurrence of the pandemic. Firstly, the distribution model of medical supplies is established based on the relevant data of this case. Since the total supply and demand of medical materials is 210 and 420 tons, the actual supply quantity of medical materials for hospital ①, ②, ③, ④, and ⑤ should be 60, 50, 40, 30, and 30 tons, respectively. Moreover, all the vehicles must transport for the first round. The brief solving process of the problem based on the multiple dynamic programming algorithm is as follows.

There are two possible cases for the first phase including “1_1_1” ($i = 1, j = 1, k = 1$) which represents the transportation of vehicle V1 belonging to Wuhan airport in round 1, and 2_1_1 ($i = 2, j = 1, k = 1$), which represents the transportation of vehicle V3 belonging to Wuhan railway station in round 1. The state at the end of this phase is that of the final phase which is (110, 100; 60, 50, 40, 30, 30). Because the remaining supplies of the airport and the remaining demand of each hospital are greater than the carrying capacity of the vehicles, the vehicles can supply to any one of the hospitals in this phase. The supply quantity is the carrying capacity of the vehicles. Additionally, the corresponding transport time $t(S_{111}, X_{111})$ and $t(S_{211}, X_{211})$ can be obtained in Table 3. Moreover, this phase has $T(S'_{111}) = 0, t'_{111} = 0$, or $T(S'_{211}) = 0, t'_{211} = 0$. Consequently, the calculation results of each variable in the first phase are listed in Table 4.

Corresponding to the two cases for the first phase, there are also two cases for the second phase, which are 2_1_1 and 1_1_1. The state at the end of this phase is the state at the beginning of the first phase which has 5 possible conditions. After the calculation of the second phase is accomplished, the first round of transportation for all the vehicles is completed. Moreover, the vehicle V3 and V4 are considered as having made the first round of transportation, but not loaded with medical materials, for 60 and 120 min, respectively.

The third and its subsequent phases are analyzed based on the calculation results of the second phase. There are 4 possibilities for the third phase, which is choosing any one of the 4 vehicles. In the subsequent phases, if the remaining medical materials in a distributing center are 0, then the vehicles belonging to this distributing center are not considered in the subsequent phases. Overall, the supplies transportation from the airport consists of 4 or 5 phases, and there are 12 possible permutations from the third phase to the final phase; the supplies transportation from the railway station consists of 3 or 4 phases, and there are 5 possible permutations from the third phase to the final phase. Thus, the total number of phases is 7, 8, or 9, while the number of possible permutations of the phases is 504. By calculating the total time of each permutation, the minimum value, namely the shortest time of medical supplies transportation, can be obtained.

The optimal solution for this case is as follows. Vehicle V1 transports for 3 rounds consuming 156 min. It supplies 30 tons of medical materials each to hospital ① for 2 rounds, and hospital ⑤ for 1 round. Vehicle V2 transports for 1 round consuming 138 min, in which it supplies 20 tons of medical materials to hospital ④. Vehicle V3 transports for 2 rounds consuming 88 min, in which it supplies 25 tons of medical materials each to hospital ②. Vehicle V4 transports for 1 round consuming 181 min, in which it first supplies 40 tons of medical materials to hospital ③ and then 10 tons to hospital ④. In summary, the minimum time required for all the medical supplies to be transported is expected to be 181 min.

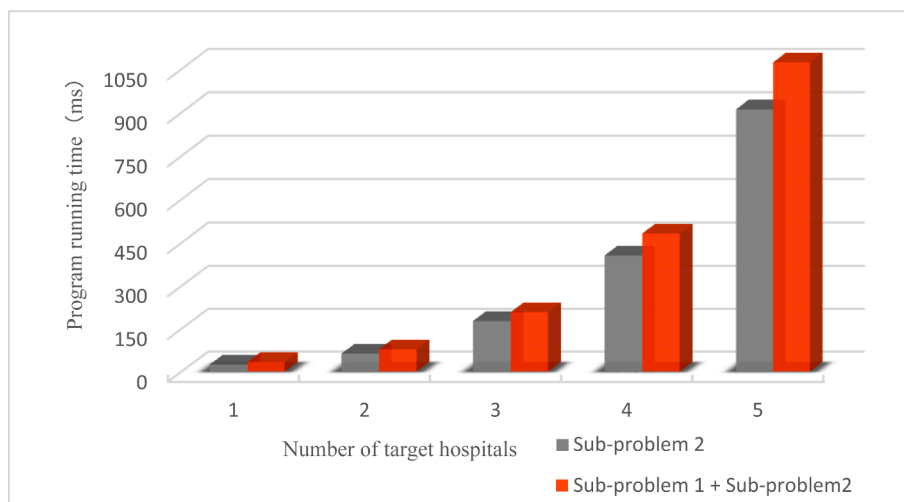


Fig. 6. Running time comparison.

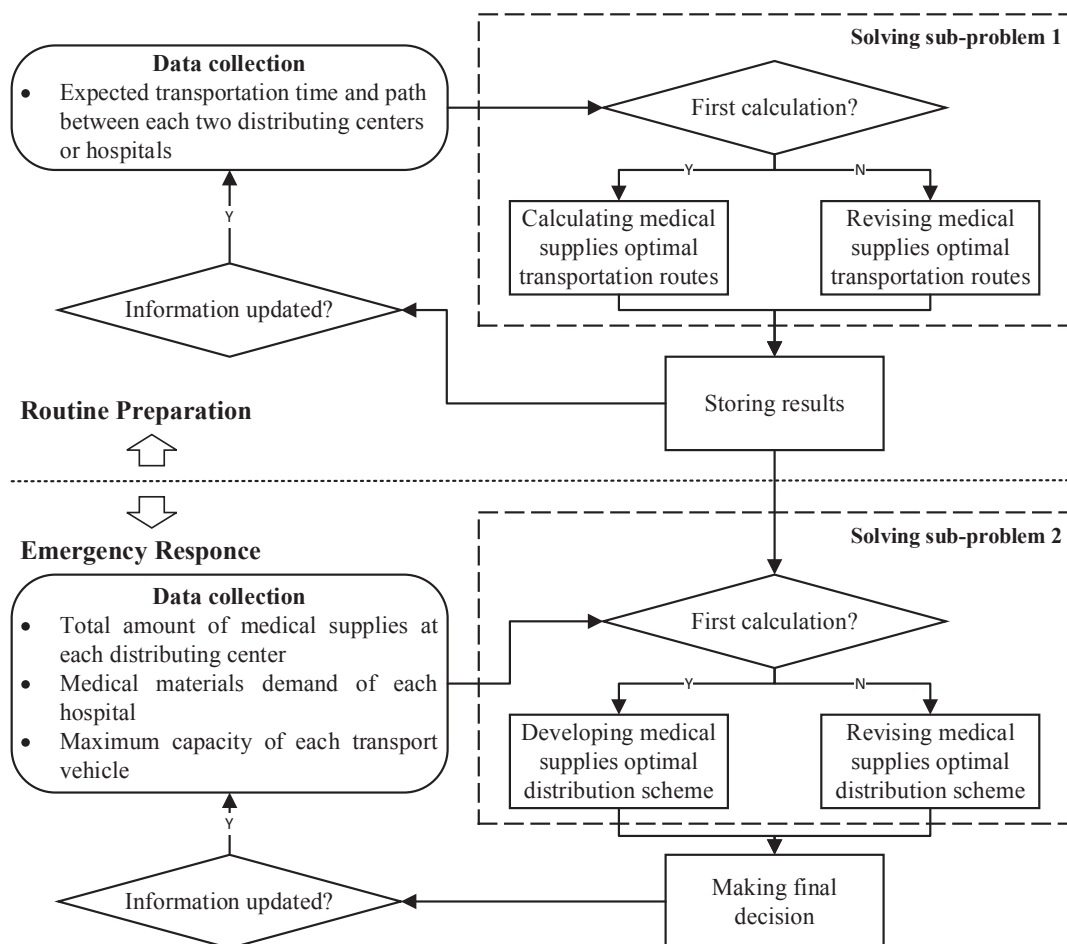


Fig. 7. Management actions for emergency logistics operations managers.

5.4. Discussion and managerial insights

The running times of the two sub-problems solution in different numbers of target hospitals, in this case, are demonstrated in Fig. 6. A comparison is made between the running time while integrating the two sub-problems (hereinafter referred to as “time 1”) and that of sub-problem 2 only (hereinafter referred to as “time 2”). It can be seen from this figure that time 1 is longer than time 2 if the number of target hospitals is equal. Moreover, the growth rate of time 1 is larger than that of time 2 with the increase of the number of target hospitals. The difference value between time 1 and time 2 is the running time of sub-problem 1 which can be solved in advance rather than in an emergency scenario. Consequently, the separation of the whole medical supplies scheduling problem into two sub-problems is effective in response to major public health emergencies.

To ensure the medical supplies scheduling methods proposed in this research employed in the management practice, several important management actions should be implemented. Routine preparation of medical supplies scheduling should be made before the occurrence of major public health emergencies; emergency response to the major public health emergencies should be made after the occurrence. The management actions for logistics operations managers in response to major public health emergencies are demonstrated in Fig. 7.

In the routine preparation, the first step is to collect the expected transportation time and path between each two distributing centers or hospitals. Afterward, a new calculation of medical supplies optimal transportation routes is performed by solving sub-problem 1. The results are stored in the database. While the relative information or data is updated, the optimal transportation routes should be revised timely.

In the emergency response, the first step is to collect the total amount of medical supplies at each distributing center, the medical materials demand of each hospital, and the maximum capacity of each transport vehicle. Based on these data and the calculation results in the routine preparation, the medical supplies optimal distribution scheme can be obtained by solving sub-problem 2. While the relative information or data is updated, the optimal distribution scheme should be revised timely. Based on the calculation results, the managers can make the final decision of medical supplies scheduling in major public health emergencies.

6. Conclusions

The current research on the scheduling of relief materials in major emergencies is mainly based on the models and algorithms for the vehicle routing problem. However, this NP-Hard problem can only obtain satisfactory solutions after a long-time operation based on the data acquired after the occurrence of the emergency. Compared with other major emergencies, the characteristics of medical materials scheduling in major public health emergencies lie in the fact that the demand places (i.e. the hospitals) and the expected transportation time can be determined in advance. Therefore, this research divides the medical supplies scheduling in major public emergencies into two stages which are solved at normal times and after the occurrence of the emergency, respectively. On this basis, the optimal emergency supplies scheduling scheme can be obtained within a short time in emergency scenarios. Specifically, this research first proposes the calculation approach of the optimal transportation route of medical supplies based on the improved Dijkstra algorithm. Afterward, it proposes the distribution model of medical supplies and its multiple dynamic programming algorithm. Moreover, in the context of the changing number of vehicles, new solutions can be obtained by slight revisions of the calculating process of the algorithm without a complete recalculation. The main innovation of this research is that the optimal solutions for the problems in the two stages under reasonable assumptions can be obtained. Moreover, the analysis of time complexity implies that the algorithms proposed in this research can solve practical problems within a short time. The limitation of the methods proposed by this research is that they are possibly not fit for the scenarios with too many hospitals because the running time would be relatively long in these situations. Consequently, the possible research direction is to improve the methods and reduce the running time according to these scenarios.

CRedit authorship contribution statement

Jia Liu: Writing – original draft. **Jinyu Bai:** Writing – original draft. **Desheng Wu:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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