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# Multi-objective medical supplies distribution open vehicle routing problem with fairness and timeliness under major public health emergencies

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**Abstract**

Fair and timely delivery of supplies plays a critical role under major public health emergencies. In this paper, aiming at fairness and timeliness, an optimization model of open vehicle routing problem for medical supplies distribution is established considering the urgency of the demand. We adopt a differential evolutionary algorithm with fast non-dominated solution sorting to solve the proposed model, obtaining an approximate Pareto optimal solution set. Through the comparison of algorithms, the results showed that the differential evolutionary algorithm with non-dominated sorting is superior with a shorter runtime and more diverse solutions, while the epsilon constraint method has more accurate solutions. In the case verification, the quality of the solutions of both algorithms was within the acceptable range, but the runtime of the epsilon constraint method was too long to be applicable. The results can provide theoretical suggestions and practical guidance for decision-makers in emergency supplies distribution.

**Keywords** Major public health emergencies, Medical supplies distribution, Multi-objective evolution algorithm, Urgency of demand

## 1 Introduction

In recent years, a series of major public health emergencies, such as SARS, anthrax crisis, swine influenza, and COVID-19, have posed a serious threat to public safety. For example, about 464 million people have been infected and more than 6.06 million people have died since the outbreak of COVID-19 (WHO 2022). In addition, major public health emergencies have a huge impact on the social economy. At the beginning of COVID-19, the total number of passengers sent by the national transportation system dropped by 50.3% (Ministry of Transport, PRC 2020), and 78% of catering enterprises had no income in China (Chinese Cuisine Association 2020).

Medical supplies under major public health emergencies are mainly used to prevent epidemics and treat diseases, including masks, protective suits, goggles, disinfectants, and ventilators. The unpredictability of major public health emergencies, the low substitutability, and the high timeliness requirements of medical supplies storage have led to a shortage of emergency medical supplies (Mete and Zabinsky 2010). Moreover, population movement can easily lead to the expansion of public health emergencies and a surge in demand for medical supplies in a short time. Therefore, there is often

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an imbalance between supply and demand for medical supplies in affected areas after the major public health emergencies, and the affected areas need to rely on external supplies to meet their demands, which promotes the development of research on the optimization of medical supplies distribution to a certain extent. In the early stage of COVID-19, the situation of unreasonable distribution and delayed transportation of the supplies were also serious, causing needless deaths (Zhu et al. 2020). Based on the above, we study the distribution of medical supplies after major public health emergencies by considering fairness and timeliness. To improve the efficiency and safety of distribution, split distribution and open vehicle distribution are also considered.

This study contributes in three ways:

1. This paper studied the distribution of medical supplies under major public health emergencies, which is very necessary and valuable at present.
2. Based on split distribution, an open-vehicle routing optimization model combining fairness and timeliness was developed. The relative fairness of medical supplies distribution was improved by incorporating the urgency of demand into the measure of fairness.
3. The differential evolution algorithm introduced by the fast non-inferior solution sorting operator was proposed to find the optimal solution for the problem. Compared with the epsilon constraint method, the diversity and convergence of the algorithm were verified in this paper.

The remainder of this paper is structured as follows. Section 2 provides an overview of the related literature. A detailed problem description is presented in Sect. 3. The model formulation and steps of the algorithm are described in Sects. 4 and 5, respectively. In Sect. 6, we adopt a COVID-19 case to verify the model and algorithm. Finally, the paper ends with conclusions in Sect. 7.

## 2 Literature review

Some related studies have been conducted in the past. This section reviews the relevant literature related to our problem including emergency supplies distribution vehicle routing problems and multi-objective optimization methods respectively in this section.

### 2.1 Emergency supplies distribution vehicle routing problem

The storage and distribution are important parts of emergency rescue (Li et al. 2022; Mete et al. 2010). Many scholars and practitioners have researched demand forecasting and supply storage, calling for a reasonable amount of emergency supplies to be stored in a reasonable place (Zaza et al. 2016). However, there was insufficient research on the distribution of emergency supplies during major health emergencies (Liu et al. 2021a, 2021b), especially on the vehicle routing problem of the relief distribution. The distribution of medical supplies from the distributing center to the affected area plays an important role after the public health emergency (Patel et al. 2017; Hou and Jiang 2021).

In the existing research, many scholars have also explored the distribution objectives and constraints. For example, Li et al. 2021a) explored the optimization of medical supplies distribution under major public health emergencies through literature review and concluded that most studies were conducted to minimize total time, minimize total cost, and maximize the requirement point coverage expectation. To minimize the total delivery time of vehicles arriving in affected areas, Zhong et al. (2020) constructed a bi-objective mixed-integer nonlinear programming model. With the dual goal of minimizing carbon emissions and distribution costs, Li et al. (2021b) established a distribution path planning model with multiple distribution stations and solved it by using a hybrid genetic algorithm to achieve the balance between the two goals. Some scholars also believe that the distribution of supplies should take into account the urgency of the demand for emergency supplies in the affected areas (Rivera-Royero et al. 2016; Shamsi Gamchi et al. 2021). For humanitarian purposes, we often do not involve cost considerations in the initial stages of the public health emergency. However, the fairness and timeliness of medical supplies distribution are indispensable.

The fair distribution of medical supplies reflects the respect for the human right to survival and can avoid negative social emotions caused by unfair distribution (Rezaei-Malek and Tavakkoli-Moghaddam 2014). Therefore, fairness has been taken into consideration by many scholars (Anaya-Arenas et al. 2018; Liu et al. 2019). In reality, public health emergencies, such as epidemics, can be an easy cause of social panic (Luo et al. 2021). To avoid patients' psychological panic due to the unreasonable allocation of emergency supplies, Li and Du (2021) constructed a multi-cycle medical supplies distribution model, whose goal is to minimize the psychological panic of patients and the emergency response cost. Considering the order, Herrmann (2011) believed that in the case of overall fairness, the order in which customers were served also affected their perception of fairness. As a result, the order of visits to the affected areas is also included in the fairness measurement in this paper.

Time is a key factor in disaster response, according to key benchmarks defined by the US Federal Emergency Management Agency (Fugate 2012). Compared with other emergency supplies, medical supplies are more demanding in terms of delivery times and no delays are allowed. Zhang et al. (2020) reveal that timely distribution of medical supplies can help prevent the spread of the epidemic. In addition, Yang (2019) pointed out that the demand of the victims for medical supplies is often time-limited. Victims must receive assistance within a specific time if medical supplies are to be effective. Scholars mostly measure timeliness through total delay time, total delivery time, and the latest delivery time (Eisenhandler and Tzur 2019; Liu et al. 2021a, 2021b).

Under a major public health emergency, to improve the efficiency and safety of delivery, vehicles should stop in the last affected area and wait for the next order (Li et al. 2021a, 2021b). Then, the distribution problem studied in this paper can be summarized as an open-vehicle routing problem (OVRP). In addition, in the early stage of the outbreak, the quantity of material distribution was large, and single vehicle distribution could not meet the requirements of distribution, which made it necessary to consider split distribution. There are some in-depth studies on the emergency supplies distribution vehicle routing problem under major public health emergencies, and the characteristics of the studies are summarized in Table 1.

As can be seen from Table 1, few articles consider both fairness and timeliness under major public health emergencies. Therefore, based on considering the urgency of demand, we consider the fairness and timeliness of the distribution of medical emergencies supplies in this paper. Among them, fairness is measured by the total demand satisfaction rate gaps among the affected areas. Limited emergency supplies ideally should be prioritized for those affected areas with more urgent demand to improve fairness. In addition, timeliness is measured by the total delivery time.

### 2.2 Multi-objective optimization methods

In terms of solving multi-objective optimization problems, the linear weighted sum method is simple and convenient to use. However, studies have shown that the solution of the weighted model does not correspond to the real solution of the original model (Du 2015), and it also has disadvantages such as strong subjectivity and long calculation time. As an accurate algorithm, the epsilon constraint method is also widely used in multi-objective optimization problems (Fan et al. 2016). Through literature analysis, it is found that more studies are solved by heuristic algorithms and intelligent algorithms (Eisenhandler and Tzur 2019; Sheng et al. 2019; Kang et al. 2020; Karami et al. 2020). The heuristic algorithm includes simulated genetic algorithm (GA), ant colony algorithm (ACO), differential evolution algorithm (DE), and so on (Nayeri et al. 2022), which can often find a good solution in one time, but in some special cases, the efficiency of solving can't be guaranteed. To ensure the efficiency of solutions, scholars often improve algorithms

**Table 1** Research on the emergency supplies distribution vehicle routing problem under major public health

| References | Disasters types | Materials types | Objectives | | Consideration | | Solving method |
|---|---|---|---|---|---|---|---|
| | | | Fairness | Timeliness | Open-vehicle routing | Split delivery | |
| Liu et al. ( 2021a, 2021b) | Major public health emergency | Medical supplies | × | √ | × | √ | Multiple dynamic programming algorithm |
| Du et al. (2022) | Major public health emergency | Medical supplies | × | √ | × | × | Column generation and pulse algorithm |
| Zhong et al. (2020) | Generalized disasters | Generalized supplies | × | √ | × | × | Hybrid genetic algorithm |
| Chen et al. (2020) | COVID-19 | Food | × | √ | × | √ | PEABCTS algorithm |
| Akwafuo et al. (2020) | Public health emergencies | Generalized supplies | × | √ | √ | × | Hybrid heuristic algorithm |
| Liu et al. (2020) | COVID-19 | Medical waste | × | √ | × | × | Ant colony-tabu hybrid algorithm |
| Li et al. (2020) | Public health emergencies | Emergency supplies | × | √ | √ | √ | NSGA-II algorithm |
| Ning et al. (2021) | Public health emergencies | Medical material | × | √ | × | × | Heuristic algorithm |
| Shiri et al. (2022) | COVID-19 | Vaccine | √ | × | √ | √ | Multi-stage stochastic programming |
| This paper | Major Public Health Emergencies | Medical supplies | √ | √ | √ | √ | NSDE algorithm |

according to practical problems. For example, the Dijkstra algorithm is often used to solve the shortest path problem, and Liu et al. (2021) have proposed a multi-dynamic programming algorithm based on the improved Dijkstra algorithm to solve the distribution of medical supplies in major public health emergencies. With long calculations, the algorithm does not apply to the distribution of medical supplies at the initial stage of an emergency, which this paper aims to solve.

The optimization effect of the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) is better, which can get all the optimal solutions at one time, and has the advantages of good convergence, fast operation, and local search (Deb et al. 2002; Murugan et al. 2009). In addition, NSGA-II does not need to assign the target weight, which can avoid the subjective preference of weight assignment. By comparing Non-Dominated Sorting Differential Evolution (NSDE) with a weighted genetic algorithm, Du (2015) concluded that NSDE had certain advantages in solving multi-objective models. NSGA-II and NSDE are similar in structure, and perform better in the diversity mechanism and elite retention mechanism. In this paper, the NSDE with strong operability will be selected to solve the model.

## 3 Problem definition

This paper focuses on the distribution of non-targeted medical supplies in the initial stage of major public health emergencies. Different from government-directed distribution, the social non-targeted medical supplies were mainly donated by organizations, companies, and individuals for the major public health emergencies, which are not designated to the specific affected areas and need to be distributed scientifically. Thus, the research object of this paper is social non-targeted medical supplies, which is referred to as medical supplies for short.

Therefore, there are four cores of the problem definition in this paper. (1) after a public health emergency, medical supplies need to be distributed to affected areas as quickly as possible to reduce the negative impact; (2) faced with limited medical supplies and vehicles, managers also need to distribute them fairly to reduce social discontent; (3) to ensure the efficiency of distribution and reduce the infection of drivers, the vehicle will not return the distribution centers after the last delivery, but stay in the last place and wait for the next assignment; (4) each affected area can be served multiple times by multiple vehicles, but only once by the same vehicle.

To visualize the problem, the distribution network of medical supplies under major public health emergencies can be defined as $G = (N, Y)$ shown in Fig. 1, where $N$ is the set of nodes, and $Y = \{(i,j) : i,j \in N, i \neq j\}$ is the set of feasible links in the network. $N$ contains two subsets:

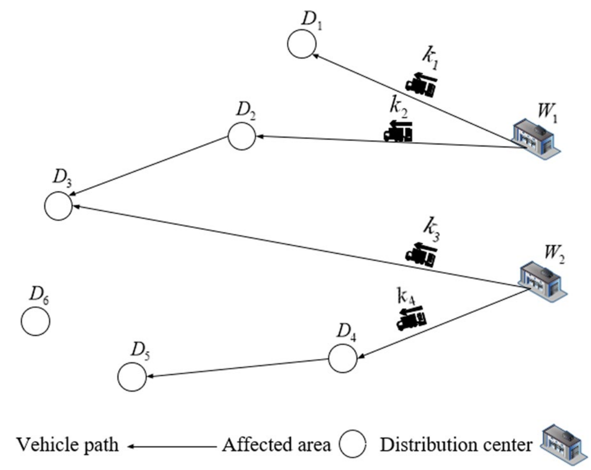


**Fig. 1** An illustration of vehicle routing problem in relief distribution

$W$ represents the set of distribution centers and $D$ is the set of affected areas. The number of vehicles available in each distribution center is known, and all vehicles are parked at the last affected area after the delivery. A fleet of homogeneous vehicles $K$ with capacity $C$ departs from the distribution centers $i$ $(i \in W)$ to provide medical material distribution services to the affected area $j$ $(j \in D)$.

In conclusion, in line with the principle of improving fairness and timeliness, the following decisions should be made: (1) given a set of distribution centers and vehicles, what quantity of medical supplies should those vehicles carry to which affected areas so as to maintain fairness between the affected areas; (2) in which order will these vehicles visit the affected areas from the distributions to deliver the supplies as timely as possible.

## 4 Model formulation

To better characterize the model, the following assumptions are proposed: (1) the location information of each node in the network is known, and the distance between each node can be obtained through Baidu map distance measurement; (2) vehicles are considered for medical material distribution, and other transportation methods are not considered; (3) the time for vehicles to load and unload supplies in any area is short and negligible; (4) the demand for medical supplies is far greater than the available quantity.

Considering the fairness and timeliness of medical supplies distribution under major public health emergencies, an open dual-objective optimization vehicle routing problem model is developed. The meanings of indices, sets, parameters, and variables adopted in the model are described in Table 2.

**Table 2** Notations and definitions in the model

| Item | Description |
|---|---|
| Indices | |
| $i, j$ | Indices to nodes, $i, j \in N$ |
| $k$ | Indices to vehicles, $k \in K$ |
| Sets | |
| $G$ | The distribution network |
| $N$ | Set of all nodes in the distribution network |
| $Y$ | Set of all feasible links in the distribution network |
| $W$ | Set of all distribution centers |
| $D$ | Set of all affected areas |
| $K$ | Set of all vehicles |
| Parameters | |
| $c$ | The capacity of a vehicle |
| $d_{ij}$ | Distance of feasible link $(i, j), i, j \in N$ |
| $v$ | Speed of the vehicles $k, k \in K$ |
| $h_i$ | The urgency of demand of the affected area $i, i \in D$ |
| $R_i$ | Quantity of supplies needed by the affected area $i, i \in D$ |
| $k^*$ | Number of vehicles available for delivering medical supplies |
| $s$ | Number of affected areas |
| Variables | |
| $Y_i$ | Quantity of supplies delivered by all vehicles to the affected area $i, i \in D$ |
| $v_{kij}$ | 1, if the vehicle $k$ travels from area $i$ to $j (i \neq j)$; 0, else, $i, j \in N$ |
| $I_{kij}$ | Quantity of supply carried by vehicle $k$ directly from area $i$ to $j, k \in K, i, j \in N$ |
| $L_{ki}$ | 1, if the affected area $i$ is the last affected area served by vehicle $k$; 0, else, $i \in D, k \in K$ |

### 4.1 Objective function

(1) Minimize the total demand satisfaction rate gap

After a major public health emergency, there is an urgent demand for medical supplies in the affected areas, but the existing medical supplies cannot meet the demand in a short period. Therefore, the fairness theory is introduced to make the demand satisfaction rates in the affected areas as close as possible. And the more urgent demand in an affected area is, the higher proportion of the demand satisfaction rate in the affected areas in the fairness evaluation will be.

Let $F$ expresses the total demand satisfaction rate gap in the affected areas considering the urgency of demand. Equation (1) indicates the minimization of the sum of the demand satisfaction rate gap, where $g_i$ denotes the demand satisfaction rate of the affected areas $i(i \in \mathrm{D})$ and $\overline{g}$ means the average demand satisfaction rate of all affected areas.

$$\min F = \sum_{i \in D} h_i (g_i - \overline{g})^2. \tag{1}$$

$$g_i = \frac{Y_i}{R_i}, \quad \mathrm{i} \in \mathrm{D}. \tag{2}$$

(2) Minimize the total delivery time

The delivery of medical supplies under the major public health emergencies has a higher requirement on timeliness, so timeliness is also included in the decisive goal. Let $E$ represents the total delivery time, which can be calculated by the sum of the product of all units of medical supplies and their delivery time. The shorter the total delivery time, the higher the timeliness of delivery. Therefore, the second objective function can be expressed as:

$$\min E = \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} v_{kij} I_{kij} \frac{d_{ij}}{v}, \quad i \neq j. \tag{3}$$

### 4.2 Constraints

$$\sum_{i \in D} h_i = 1. \tag{4}$$

$$\sum_{i \in D} Y_i = k^* C. \tag{5}$$

$$\sum_{i \in N} v_{kij} \leq 1, \forall k \in K, \forall \mathrm{i}, j \in N, i \neq j. \tag{6}$$

$$\sum_{i \in D} L_{ki} = 1, \forall k \in K. \tag{7}$$

$$\sum_{j \in N} v_{kij} - \sum_{j \in N} v_{kji} = 0, \forall i \in N \backslash \{i | L_{ki} = 1\}, \forall k \in K. \tag{8}$$

$$0 \leq I_{kij} \leq C, \forall k \in K, \forall i, j \in N. \tag{9}$$

$$Y_i \leq R_i, \forall i \in D. \tag{10}$$

$$v_{kij} \in \{0, 1\}, \forall k \in K, \forall i, j \in N, i \neq j. \tag{11}$$

$$Y_i, R_i \geq 0, \forall i \in D. \tag{12}$$

Constraint (4) indicates that the sum of the urgency of demand of all affected areas equals 1. Constraint (5) means that the medical supplies loaded in vehicles must be delivered to affected areas. Constraint (6) represents that the same vehicle can only visit an affected area at most once. Constraint (7) mean that the vehicle can stay at only one node after the delivery. Constraint (8) represents the vehicle flow balance constraint, which indicates that a vehicle needs to leave from a node other than the final node on its delivery route after reaching that node. Constraint (9) refers to the vehicle capacity constraint. It means that the vehicle does not deliver more materials than its capacity. Constraint (10) indicates that the supply is not greater than the demand. Constraints (11)–(12) are 0–1 constraints and non-negative constraints, respectively.

## 5 NSDE algorithm

The NSDE algorithm proposed by Angira et al. (2005) extends the Differential Evolution (DE) algorithm to multi-objective optimization problems and is widely used in solving multi-objective optimization problems. The process of using the NSDE algorithm to obtain an approximate Pareto optimal solution set can be seen in Fig. 2, where *NP* represents the population size, and each chromosome in the population represents a distribution plan of the medical supplies. In addition, three key steps of the DE algorithm are described below.

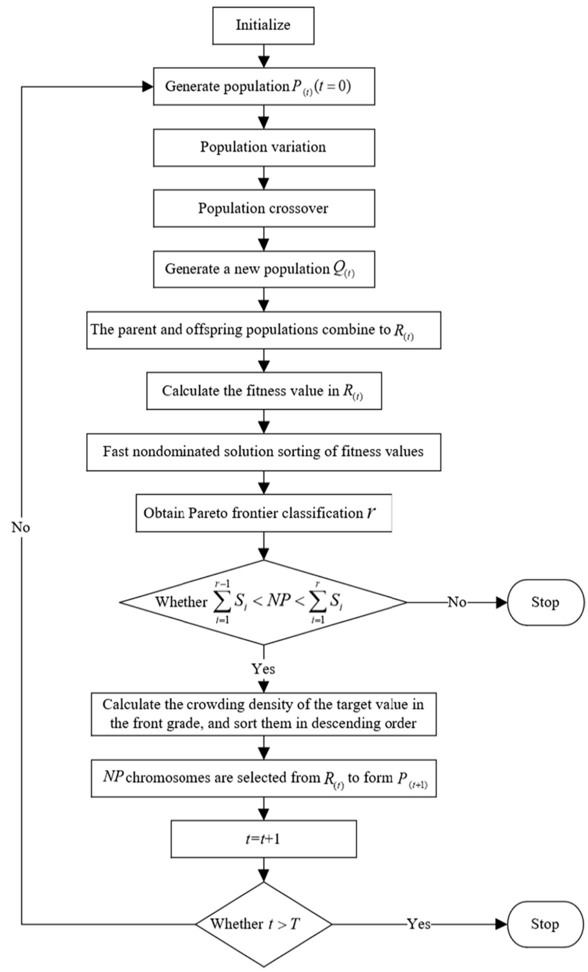


**Fig. 2** NSDE algorithm process

The meanings of symbols involved in the NSDE algorithm process are described as follows: $F_i$ represents the set of solutions in the frontier $i$, $S_i$ represents the number of chromosomes in the frontier $F_i$ of Pareto; $T$ is the maximum allowed number of iterations.

### 5.1 Coding and initializing chromosomes

Each chromosome in this paper is composed of two sub-strings, that is $X_i = [X_i^1, X_i^2]$. String 1 is the random arrangement of vehicles, and string 2 is the random arrangement of affected areas, that is $X_i^1 = randperm(k^*)$, $X_i^2 = randperm(s)$. The chromosome length is $k^* + s$, and the population size is $NP = 5 * (k^* + s)$ (Storn 1996). For example, when $k^* = 4$, $s = 6$ and $i = 1$, the random arrangement of vehicles in string 1 is $X_1^1 = randperm(k^*) = [3, 4, 1, 2]$, and the random arrangement of affected areas in string 2 is

$X_1^2 = randperm(s) = [5, 4, 2, 6, 1, 3]$. The chromosome $i = 1$ is $X_1 = \left[X_1^1, X_1^2\right] = [3, 4, 1, 2, 5, 4, 2, 6, 1, 3]$.

The coded data needs to be encoded. The encoding process is as follows: the first locus in string 1 starts from the distribution center and accesses the first locus in string 2. If there are any medical supplies left, the next locus of string 2 is visited. Otherwise, it stays at this locus in string 2. The second locus of string 1 is distributed from the next locus of string 2. And so on. When there is a surplus in string 1 and the string 2 locus are not all satisfied, the process is repeated.

### 5.2 Variation and crossover

Variation operation is to generate new solutions through individual gene changes. The variation operation of the traditional Genetic Algorithm (GA) will cause the solution to fall into the local optimum, so the DE algorithm is improved. The variation operation of the NSDE algorithm in this paper is to add the weighted difference of any two individuals in the chromosome population to the third chromosome to produce the variation vector $V_i$. After the weighted difference, the value of gene position in the chromosome string may be out of bounds, so the largest-order-value ($LOV$) rule is used to correct it (Qian et al. 2009). For example, assume that there are six affected areas, and after weighted difference, the variation vector $V_i$ of string 2 in the chromosome $i$ is $[-5.7, 4.6, 2.9, -6.4, 1.3, 3.1]$. After the correction of LOV, the maximum value in the variation vector $V_i$ is given 6, followed by 5 for the second largest value, 4 for the third largest value, and so on. Finally, the modified variation vector $V_i$ becomes $[2, 6, 4, 1, 3, 5]$.

The crossover operation is designed to randomly generate new individuals in a probabilistic manner. Binomial crossover is used to generate the test vector $U_i$ in this paper. When the value of the crossover rate ($CR$) is less than the random number, the value in the target chromosome $X_i$ is assigned to $U_i$; otherwise, the value of $V_i$ is assigned to $U_i$. Where, $CR = 1 - t/Maxgen$, generated by the adaptive method, and the value is between 0 and 1. For example, assuming that $X_i = [3, 4, 1, 2, 5, 4, 2, 6, 1, 3]$ and $V_i = [3, 4, 2, 1, 2, 6, 4, 1, 3, 5]$, when $CR$ is less than the random number, then $U_i$=[3, 4, 1, 2, 5, 4, 2, 6, 1, 3], otherwise $U_i$=[3, 4, 2, 1, 2, 6, 4, 1, 3, 5].

### 5.3 Elite selection mechanism

An elite selection mechanism can retain the optimal individuals produced in evolution and finally get the global optimal solution. This paper is mainly based on fast non-dominated solution sorting and crowded density sorting to select elite individuals.

Fast non-dominated solution sorting. The non-dominated solution is also called the Pareto solution, which is a multi-objective solution that is not dominated by other solutions proposed by Pareto in 1986. Fast non-dominated solution sorting can accelerate the convergence rate of the algorithm. The chromosomes in the population are sorted according to the two target values, and then the Pareto front rank to which the chromosomes belong is obtained. $p$ is the dominant solution, $S_p$ is the set of dominated solutions dominated by $p$, and $N_p$ is the number of $p$.The fast non-dominated solution sorting method is proposed by Deb et al. (2002), whose pseudo code can refer to Wang's research (Wang et al. 2014).

Crowded density sorting. The crowding density refers to the density of solutions in the same layer of non-dominated solutions, which needs to be considered to ensure the diversity of the population. Suppose the distances between a solution and its nearest $NP$ solutions are $d_1, d_2, d_3, \ldots, d_{NP}$, then its crowding density is $d = NP/\left(1/d_1 + \cdots + 1/d_{NP}\right)$.

## 6 Case study

COVID-19 poses significant challenges for supplies management under major public health emergencies (Cao et al. 2020). Therefore, the distribution of medical supplies in Province X during the COVID-19 was taken as an example in this paper. We studied the distribution of surgical masks from 00:00 to 24:00 on February 4, 2020. The Red Cross (0) served as the distribution center for supplies, with a lot of medical supplies stored. And the locations of the distribution center and affected areas (1–17) are shown in Fig. 3, where the size of the points reflects the demand of the affected areas. In the distribution network, distance data of all regions are shown in Table 3. In addition, the data on the number of surgical masks in the affected area is available from the government website, as shown in Table 4.

Assuming that at the initial stage of emergency response, there are 750,000 surgical masks in the

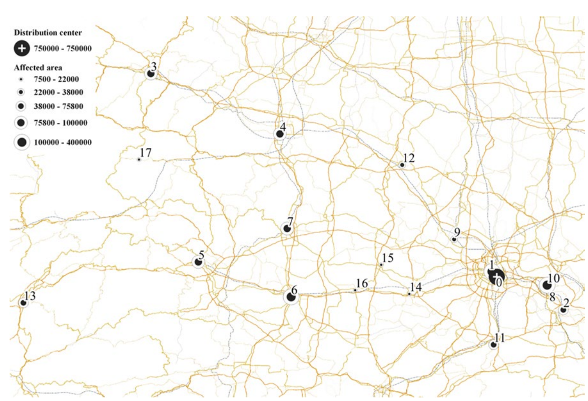


**Fig. 3** Location maps of distribution centers and affected areas

distribution center and only 16 emergency vehicles with the capacity of 50,000 surgical masks and the driving speed of 50 km/h. The urgency of demand of each affected area are as follows: $h_i$=[0.2600, 0.0453, 0.0667, 0.0853, 0.0733, 0.0813, 0.0453, 0.0160, 0.0640, 0.0827, 0.0440, 0.0280, 0.0547, 0.0187, 0.0147, 0.0147, 0.0053].

Based on the relevant data of the COVID-19, this paper tries to find the optimal distribution solutions on the premise of satisfying the fairness and timeliness of supplies distribution in the affected areas.

### 6.1 Computational results

Using $R$ software to run the algorithm, a more ideal solution set was obtained. In which, the maximum operation algebra $\max gen = 500$, the variation parameter $F = 0.5$ is obtained through continuous testing. After solving the model, six approximate optimal solutions in the solution set of Pareto front 1 are obtained, as shown in Table 5. The specific values of the solution with the best timeliness and fairness are shown in Table 6.

The specific vehicle routes and distribution schemes of the above two solutions (Solution 6 and Solution 1) are shown in Figs. 4 and 5. From the perspective of optimal fairness, compared with the solution with the best timeliness, the demand satisfaction rate of each affected area is mostly maintained at about the average demand satisfaction rate (0.7792). As can be seen from Table 4, except for the affected area 1 and the affected areas with a demand satisfaction rate of 1, the demand satisfaction rates of the other affected areas in this solution are all distributed between 0.5 and 0.85, without a large gap. Therefore, this solution is relatively fair. From the perspective of optimal timeliness, it has the shortest total delivery time per unit of supply. Eight vehicles in solution 6 visited only

**Table 3** Distance between the affected areas

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | | | | | | | | | | | | | | | | | |
| 1 | 9.1 | 0 | | | | | | | | | | | | | | | | |
| 2 | 95 | 83.1 | 0 | | | | | | | | | | | | | | | |
| 3 | 449 | 403.8 | 488.8 | 0 | | | | | | | | | | | | | | |
| 4 | 321 | 261.3 | 343.4 | 143.2 | 0 | | | | | | | | | | | | | |
| 5 | 324 | 290.8 | 364.5 | 221 | 166.4 | 0 | | | | | | | | | | | | |
| 6 | 223 | 201.2 | 270.5 | 289.8 | 186.2 | 99.1 | 0 | | | | | | | | | | | |
| 7 | 247 | 208 | 287.7 | 223.7 | 180.3 | 94.5 | 78.2 | 0 | | | | | | | | | | |
| 8 | 76 | 57.4 | 27.4 | 459.2 | 317 | 346.8 | 254.9 | 266.5 | 0 | | | | | | | | | |
| 9 | 67 | 49.1 | 131.7 | 355.2 | 213.4 | 255.7 | 176.9 | 167.8 | 104.9 | 0 | | | | | | | | |
| 10 | 71 | 55.9 | 32.8 | 457.8 | 314.3 | 344.6 | 252.5 | 262.5 | 5.6 | 101.7 | 0 | | | | | | | |
| 11 | 88 | 83.9 | 79.4 | 457.2 | 321.1 | 306 | 207.8 | 244.5 | 80.2 | 124.3 | 83.6 | 0 | | | | | | |
| 12 | 178 | 150.2 | 229.2 | 264.9 | 124,2 | 228.8 | 186.1 | 133.8 | 201.4 | 103.7 | 197.8 | 224.2 | 0 | | | | | |
| 13 | 526 | 467.6 | 536.2 | 287.8 | 316.2 | 180.4 | 266.3 | 273.2 | 519.1 | 434 | 517.6 | 469.6 | 403.1 | 0 | | | | |
| 14 | 106 | 87.7 | 154.6 | 361.9 | 225.6 | 211.6 | 116.3 | 144 | 137.4 | 80.9 | 136.9 | 100.2 | 151.9 | 381.9 | 0 | | | |
| 15 | 147 | 109.9 | 187.1 | 315.8 | 182.5 | 180.9 | 96.1 | 101.1 | 166 | 79.5 | 165 | 143.2 | 117.7 | 357.6 | 44.7 | 0 | | |
| 16 | 158 | 138.3 | 208.8 | 315.9 | 192.6 | 157.3 | 62.1 | 94.8 | 191.4 | 116 | 189.9 | 153.5 | 149 | 329.2 | 53.9 | 36.9 | 0 | |
| 17 | 497 | 369.5 | 450.2 | 97.3 | 140.6 | 130.2 | 216.7 | 165.1 | 428.5 | 324.9 | 425 | 408.3 | 256 | 196.9 | 308.4 | 266.9 | 257.7 | 0 |

**Table 4** Demand for surgical masks in affected areas

| Area | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quantity demanded (thousands) | 400 | 50 | 100 | 100 | 95 | 110 | 85 | 30 | 81 | 121 | 50 | 30 | 62 | 20 | 19.2 | 18 | 7.5 |

**Table 5** The target value of pareto frontier 1 under dual objectives

| Solution | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Fairness | 0.1157 | 0.1047 | 0.1171 | 0.1431 | 0.1028 | 0.1012 |
| Timeliness | 72.7600 | 73.6680 | 78.8940 | 79.8080 | 94.5060 | 108.2740 |

**Table 6** Single objective optimal solution in pareto frontier 1

| | | Best fairness (solution 6) | | Best timeliness (solution 1) | |
|---|---|---|---|---|---|
| Fairness | | 0.1012 | | 0.1157 | |
| Timeliness | | 108.2740 | | 72.7600 | |
| Average demand satisfaction rate | | 0.7792 | | 0.7723 | |
| **Affected area** | **The urgency of demand** | **Vehicle** | **Demand satisfaction rate** | **Vehicle** | **Demand satisfaction rate** |
| 1 | 0.2600 | (12,15) | 0.2500 | (11,12) | 0.2500 |
| 2 | 0.0453 | (14) | 0.6000 | (10) | 1.0000 |
| 3 | 0.0667 | (1,4) | 0.6250 | (13) | 0.5000 |
| 4 | 0.0853 | (7) | 0.5000 | (6,4) | 0.8080 |
| 5 | 0.0733 | (5) | 0.5263 | (8) | 0.2579 |
| 6 | 0.0813 | (6,16) | 0.6364 | (1) | 0.4545 |
| 7 | 0.0453 | (10,13) | 0.8235 | (14,15) | 0.9412 |
| 8 | 0.0160 | (1) | 1.0000 | (5) | 0.6667 |
| 9 | 0.0640 | (8) | 0.6173 | (3) | 0.6173 |
| 10 | 0.0827 | (11,9) | 0.6678 | (2) | 0.8264 |
| 11 | 0.0440 | (4,2) | 1.0000 | (7) | 1.0000 |
| 12 | 0.0280 | (13) | 1.0000 | (5) | 1.0000 |
| 13 | 0.0547 | (3) | 1.0000 | (9) | 0.8065 |
| 14 | 0.0187 | (14) | 1.0000 | (15) | 1.0000 |
| 15 | 0.0147 | (9) | 1.0000 | (4) | 1.0000 |
| 16 | 0.0147 | (16) | 1.0000 | (8) | 1.0000 |
| 17 | 0.0053 | (2) | 1.0000 | (8) | 1.0000 |

one affected area, while 12 vehicles in solution 1 with the best timeliness did so, indicating that direct delivery can save time. Therefore, reducing the number of each vehicle visiting the affected area can improve the delivery timeliness.

## 6.2 Comparative results

(1) Advantages of NSDE algorithm

The epsilon constraint method usually keeps the most important one among multiple objectives and brings the rest into the constraint condition, which has a wide application in solving multi-objective problems (Abounacer et al. 2014), The comparison of the epsilon constraint method and the NSDE algorithm in the example of province X demonstrates the superiority of the NSDE algorithm. Transform into a single objective linear model. This paper argues that fairness is the most important goal of material distribution. Therefore, let $E = \varepsilon_1$, where $\varepsilon_1$ can take all the values of $E$, and add the constraint $E \leq \varepsilon_1$. The constraints (4)–(13) in the original model remain unchanged. Then the original model is transformed into a linear model.

$$\min F = L \tag{13}$$

$$\sum\nolimits_{k\in K}\sum\nolimits_{i\in N}\sum\nolimits_{j\in N} v_{kij}I_{kij}\frac{d_{ij}}{v} \leq \varepsilon_1 \tag{14}$$

Solve the single objective optimization model. It is calculated that the NSDE algorithm can give the global optimal solution in about 25 s, while the epsilon constraint method is obviously inferior to the NSDE algorithm because a value exceeds 48 h. In this case, the calculation time of the NSDE is significantly better than the epsilon constraint method.

Then, we reduced the data size of the case to reduce the calculation time, to compare the quality of the solutions. In the case of the halved size, 6 affected areas need to be delivered, the same as the first 6 affected areas in the previous case. The distribution center and vehicle remain unchanged. The results of the two algorithms are shown in Table 7.

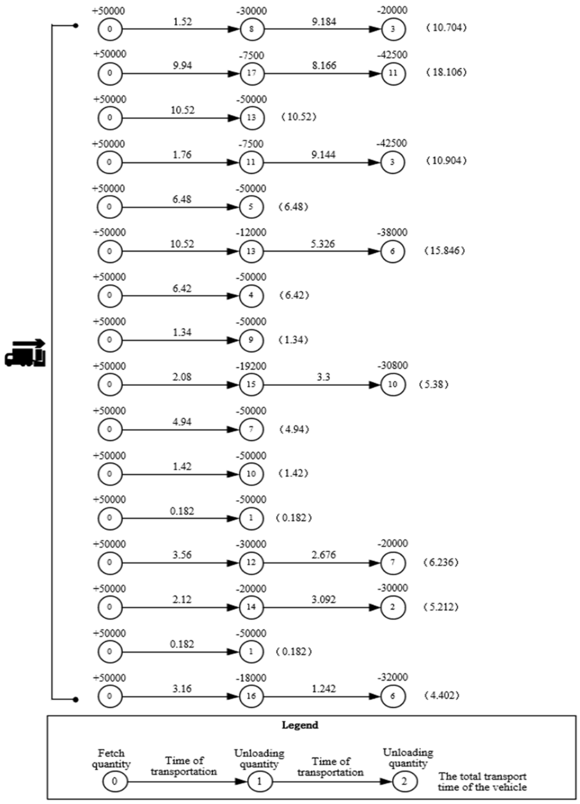


**Fig. 4** Best fairness solution

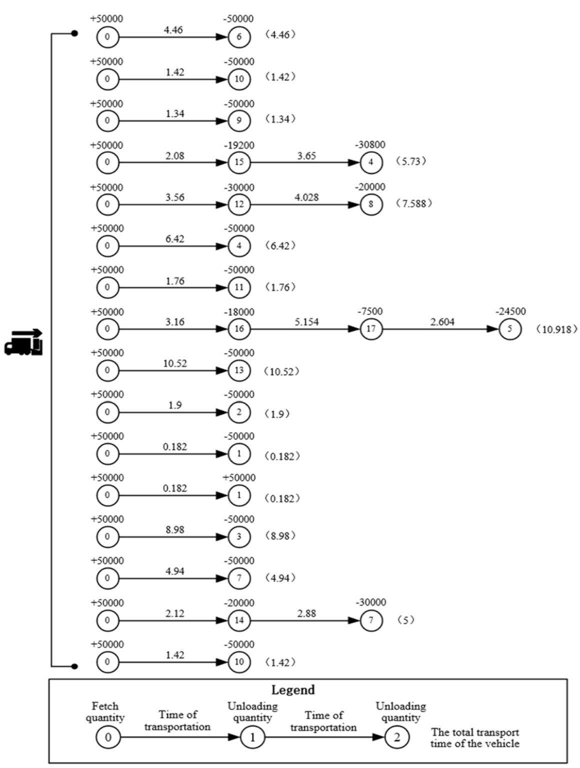


**Fig. 5** Best timeliness solution

After the operation, the NSDE algorithm obtains two approximate optimal solutions, while the epsilon constraint method obtains an optimal solution. By comparing the results, it is found that the two methods have similar results and better quality, but there is a big difference in runtime, which is similar to the conclusion of previous research (Zheng et al. 2018). The runtime of the global optimal solution of the NSDE algorithm is about 5.1487 s, while the epsilon constraint method takes 59,410.3333 s to get the global optimal solution. The comparison between the two cases shows that with the doubling of the data scale, the runtime of the epsilon constraint method is about thousands of times longer. Briefly, it can be seen that the runtime of the epsilon constraint method will increase sharply with the expansion of the data scale. In the early stage of the epidemic, medical supplies are continuously arriving at the warehouse and sent to the affected areas. Therefore, allocation decisions need to be made quickly. Furthermore, the epsilon constraint method is not applicable to the distribution decision of large-scale emergency supplies under the epidemic.

(2) Applicability of the model

A case of medical supplies scheduling in Wuhan, a city with a small-scale data, was used to verify the universality of the model. There are 13 affected areas in this case. After solving for 12 s, three optimal solutions were obtained, as shown in Table 8. The comparison proves that the model is also suitable for small-scale distribution problems.

In addition, in order to study the applicability of NSDE algorithm in large-scale data, a case involving 34 affected areas was used for comparison. It should be noted that the data in this case was randomly selected based on a map, not a real case. After about 120 s of runtime, four optimal solutions are obtained, as shown in Table 9.

The solution time and the number of optimal solutions of NSDE algorithm under different scale data are shown in Table 10. With the expansion of data scale, the runtime of NSDE algorithm is within the acceptable range. After a major public health emergency has occurred, the number of affected areas under the same level is limited. For example, emergency supplies from the municipal level are often distributed to districts and counties under their jurisdiction, while emergency supplies from districts and counties are distributed to streets and towns under their jurisdiction.

**Table 7** Comparison of the results of NSDE algorithm and epsilon constraint method

| | NSDE algorithm | | | Epsilon constraint method | | |
|---|---|---|---|---|---|---|
| | Optimal solution | Runtime/s | Optimal solution | Runtime/s | Optimal solution | Runtime/s |
| Results | $E_1$ | 0.7420 | 5.1487 | E | 0.7420 | 59,410.3333 |
| | $F_1$ | 0.0055 | | | | |
| | $E_2$ | 0.7540 | | F | $0.2821e^{-14}$ | |
| | $F_2$ | 0.0044 | | | | |

**Table 8** The target value of Pareto frontier 1 under dual objectives (smaller scale data)

| Solution | 1 | 2 | 3 |
|---|---|---|---|
| Fairness | 0.0236 | 0.0221 | 0.0183 |
| Timeliness | 1.7100 | 2.0980 | 2.1020 |

**Table 9** The target value of Pareto frontier 1 under dual objectives (larger scale data)

| Solution | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Fairness | 0.1981 | 0.1601 | 0.1431 | 0.1819 |
| Timeliness | 5.6920 | 6.3460 | 11.3480 | 5.8320 |

**Table 10** Comparison of NSDE algorithm solution in different scale data

| | | | | |
|---|---|---|---|---|
| The number of affected areas | 6 | 13 | 17 | 34 |
| Runtime/s | 5.1487 | 12 | 25 | 120.368 |
| The number of optimal solutions | 2 | 3 | 6 | 4 |

## 7 Conclusions

This paper studies the optimal distribution of medical supplies during the initial stage of major public health emergencies. For the difference between medical supplies and general supplies, as well as the difference between the major public health emergencies and general emergencies, the optimal model of medical supplies distribution under major public health emergencies is established by considering the two goals of fairness and timeliness. Based on the open route and split distribution, the model is more consistent with the reality of major public health emergencies. Moreover, the NSDE algorithm is adopted to solve the model, and the model and algorithm are verified by a real case under the COVID-19. The results show that the designed model and algorithm can be well applied and give specific solutions, including the quantity of medical supplies distribution and the vehicle route. In addition, compared with the epsilon constraint method, it is proved that the NSDE algorithm can not only guarantee the solution efficiency, but also the solution diversity and quality. The comparison of solution results under different scale data also proves the applicability of the model. The results of the study show that the model and algorithm are reasonable and effective to provide a reference for managers.

It should be pointed out that this paper only considers single-cycle allocation model, which has certain limitations. In fact, due to the continuous supply of medical supplies and the changing classification of urgency of needs in different areas, vehicles may be distributed dynamically over multiple cycles. For further research, a multi-cycle dynamic allocation model will be considered.

**Abbreviations**

| | |
|---|---|
| COVID-19 | Coronavirus Disease 2019 |
| WHO | World Health Organization |
| NSGA-II | Non-Dominated Sorting Genetic Algorithm-II |
| DE | Differential Evolution |
| NSDE | Non-Dominated Sorting Differential Evolution |

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**Author contributions**
FZ and LD contributed to the algorithm, and wrote the first version. All of the authors provided critical feedback and helped shape the research, analysis, and manuscript.

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**Availability of data and materials**
The data that support the findings of this study are available from the People's Government of Hubei Province, China. Alternatively, you can get it from the corresponding author on reasonable request.

## Declarations

**Ethics approval and consent to participate**
There are no ethical issues involved.

**Consent for publication**
Not applicable.

**Competing interests**
The above authors declare that they have no competing interests.

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