Research on Emergency Material Allocation Mode of Sudden Disaster with Improved NSGA-II

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Research on emergency material allocation mode of sudden disaster with Improved NSGA-II

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Background:
In order to solve the problems of redundancy, unfairness, low satisfaction and high cost of emergency material allocation caused by unreasonable allocation effectively in the case of sudden disasters, and minimize the economic cost, punishment cost and maximizing the satisfaction rate of disaster victims, a 3-level network emergency material allocation mode based on big data is proposed in this paper.

Methods:
Taking the loss degree and the dynamic change of material demand in the disaster stricken areas as constraints, the demand forecasting, scheduling optimization, targeted allocation and disaster victims' satisfaction model based on emergency relief materials is constructed. The Sample Average Approximation method and improved NSGA-II algorithm are designed to solve the problem.

Results:
Compared with the results obtained by the improved NSGA-II, the value is significantly reduced. From the fairness evaluation results of the two model distribution schemes, the model obtained by the improved NSGA-II is more suitable for the distribution of emergency supplies with fair distribution requirements.

Conclusions:
It can be concluded that the 3-level network allocation mode and improved NSGA-II can solve emergency relief materials allocation based on big data effectively. The next step is to design scheduling model with all feasible medical supplies allocation route to improve the practicability of the model.

Abstract
In order to solve the problems of redundancy, unfairness, low satisfaction and high cost of emergency material allocation caused by unreasonable allocation effectively in the case of sudden disasters, a 3-level network emergency material allocation mode based on big data is proposed in this paper, aiming at minimizing the economic cost, punishment cost and maximizing the satisfaction rate of disaster victims. Taking the loss degree and the dynamic change of material demand in the disaster stricken areas
as constraints, the demand forecasting, scheduling optimization, targeted allocation and disaster victims' satisfaction model based on emergency relief materials is constructed. The Sample Average Approximation method and improved NSGA-II algorithm are designed to solve the problem and the effectiveness of 3-level network allocation mode and Improved NSGA-II (Non-Dominated Sorted Genetic Algorithm-II) proposed in this paper are verified through the comparison with NSGA and PSO.

Keywords. Big data; emergency relief materials allocation; Improved NSGA-II; 3-level network allocation mode

1. Introduction

In recent years, many countries around the world have experienced different types of severe natural disasters, such as the Indian Ocean tsunami, the Haiti earthquake, the snowstorm in southern China, and the U.S. Hurricane Katrina. This has caused severe economic losses and casualties in the affected areas, and has made it particularly important to optimize the allocation of emergency supplies after disaster, reduce the incidence of secondary disasters, and reduce the cost of relief materials. Emergency relief materials allocation means that after a disaster occurs, according to the degree of demand for shortage materials in the disaster area, effective response measures are taken in the shortest time to reasonably allocate various types of emergency relief materials (drinking water, food, medicine, etc.) from different emergency relief centers to different relief points in the disaster area. However, in the actual process of emergency supplies allocation, there will be asymmetry between material supply and demand information, imprecise demand prediction and real-time disaster information acquisition, etc. This will lead to excess (or shortage) of emergency relief materials, increased allocation costs and low relief efficiency. Such problems not only aggravate the loss of people in the disaster-stricken areas, but may also cause secondary disasters. In order to effectively solve the problems of redundancy, waste, low efficiency, and high cost of emergency relief materials configuration, an improved NSGA-II is proposed in this paper, which builds an emergency relief materials configuration mode based on big data and real-time information updates to achieve the goal of precise configuration of disaster emergency relief materials. The overall structure of the paper is as follows: In Section 2, some previous works are introduced and the difference from the previous works is stated. In Section 3, a mathematical model for emergency relief materials allocation for disaster is established and the detailed problem description is summarized. In Section 4, the improved NSGA-II algorithm under emergency management is proposed. In Section 5, the algorithm and the fairness of relief materials allocation are verified through the simulation model of emergency relief materials allocation in disaster area.

2. Research status

The key to the rational allocation of relief supplies by emergency management departments is to resolve the imbalance between the scarcity of relief supplies and the excessive demand in disaster areas. Relevant scholars at home and abroad have conducted exploratory research on the allocation of emergency medical supplies from different perspectives. For example, Dodo et al. used loss estimation models to comprehensively evaluate regional risks, and used the evaluation results to provide guidance for emergency rescue resource allocation decisions. A linear program
supporting systemic regional disaster mitigation analysis was developed and verified by real earthquake cases in Los Angeles. Davidson et al. [2] further studied the allocation of emergency relief supplies on the basis of this procedure, and put forward the view that both timeliness and fairness should be taken into account in the allocation process. At the same time, it is analyzed that the emergency department needs to allocate emergency rescue materials reasonably and quickly according to the principle of first emergency and then delay, in order to maximize the effectiveness of rescue materials [3]. In the emergency management process, the way to obtain disaster big data is mainly based on online social media, which can generate massive information [4]. Yates [5] et al. have shown that social media big data has the characteristics of timeliness, multi-source and interactivity, which can effectively serve disaster emergency response and plays an important role in disaster emergency management and emergency material allocation. Dabner [6] pointed out that the use of big data for emergency material allocation can effectively reduce the loss and impact caused by disasters. Based on the Chinese Sina Weibo platform, Huan Zhu et al. [7] used text mining technology to construct an instant disaster detection system capable of extracting big data information in a timely manner to reduce disaster losses through scientific material allocation. Jiang TH et al. [8] collected big data information about sudden disasters through Baidu Index, compared and analyzed the social response stage characteristics of different types of disasters and the reasons for their differences, and then proposed emergency management strategy based on different types of sudden disasters that could effectively reduce disasters loss. Hjorth et al. [9] proposed the prediction and identification strategy of dynamic material demand based on big data, which provided an effective basis for emergency relief materials allocation. Jun-qing et al. [10] used big data from Twitter tweets during the 2011 Japanese earthquake to find that the demand for relief materials in the disaster area changed dynamically during the different relief phases after the disaster. Based on the concept of disaster big data information, Ning T et al. [11] established a disaster emergency material demand prediction model based on the safety stock model and adopted the radial basis neural network method, which provided a reference for the scientific configuration of emergency materials. Acar et al. [12] found that the relevant geographic location information carried in online disaster big data can effectively improve the efficiency of disaster relief and material allocation. Davis et al. [13] analyzed the big data in Twitter and extracted the geographic location information of disaster relief to understand the latest disaster progress in the disaster area. Feldman et al. [14] pointed out that sudden disasters usually cause serious damage to infrastructure such as telecommunications, and most affected groups will choose to use relatively solid network social media to seek help or publish relevant latest disaster information after the disaster. Other scholars conducted research from the perspective of the distribution of disaster emergency relief materials. For example, LIU Caijie et al. [15] studied the improvement of the organization and management capabilities of the distribution of relief materials from the actual situation of the distribution of emergency relief materials after the disaster, and provided professional equipment and technical support for the distribution of relief materials. T Ning et al. [16] studied the
transportation of the wounded after a sudden disaster, and designed the shortest ambulance allocation model for the overall rescue time when the number of ambulance vehicles is limited, and the corresponding relaxation algorithm. Mete et al. \cite{Mete2017} designed a stochastic planning model by using disaster scenarios to capture disaster-specific information and the possible impact of disasters, which was used to select the storage location of emergency medical supplies and the required inventory level of each kind of medical supplies. Arora et al. \cite{Arora2018} proposed the allocation method of emergency rescue resource for regional assistance in public health emergencies. Ruan et al. \cite{Ruan2019} designed a large-scale disaster relief material allocation method according to different disaster situations. Yarmand et al. \cite{Yarmand2020} designed a simulation model to capture the epidemic dynamics in each region under different vaccination levels, and defined the vaccine allocation problem as a two-stage stochastic linear programming problem, and proposed and verified an easy-to-implement heuristic vaccine distribution method. Xiang et al. \cite{Xiang2021} proposed a queuing network model to simulate the deterioration of the victim’s health after a disaster, and gave the analytical and numerical solutions of the queuing network, and then established two resource allocation models, each with the minimum total expected mortality and the minimum total waiting time as the optimization goals.

In summary, big data has been applied in the field of emergency management, but most of the relevant studies are based on macroscopic analysis of the role of big data in disaster emergency management and relief materials allocation process. Few studies have integrated big data technology and analysis methods into the whole process of emergency relief materials allocation, moreover, there is a lack of specific research on emergency relief materials configuration mode based on real-time information update of big data. Traditional emergency management research methods lack real-time information update technology of big data, which leads to problems such as the mismatch of actual supply and demand of materials, insufficient targeting ability of emergency decision-making, and insufficient emergency relief materials allocation ability. Therefore, there is an urgent need to combine big data technology to conduct research on the emergency relief materials allocation mode of emergency disasters, so as to improve the accuracy of disaster emergency relief materials allocation, and then promote the government's precise emergency management.

3. Problem modeling

3.1 Problem description

The factors affecting the allocation of emergency medical relief materials include: the number of emergency relief materials distribution centers and rescue points, the number of emergency medical relief materials, delivery conditions, and supply and demand. The primary goal of the configuration is to meet the demand of relief materials of different rescue points in the shortest possible time. In this paper, under the condition of adequate supply of emergency medical supplies after a disaster, multiple decision-making objectives such as multiple distribution centers, multiple relief points, time cost, economic cost and fairness were comprehensively considered.
The problem is described as follows: after the disaster occurs, distribution centers of emergency medical relief materials of appropriate scale and quantity are established around the disaster area, the relief materials are transferred from the distribution centers to the temporary logistics centers, and then appropriate distribution methods are selected to supply the relief materials from the logistics centers to different relief points. Suppose there are \( p \) emergency logistics centers \( L_1, L_2, \ldots, L_p \), the emergency medical relief material reserves of each logistics center are corresponding to \( c_1, c_2, \ldots, c_p \); There are \( k \) rescue points \( R_1, R_2, \ldots, R_k \), the demand for emergency medical relief materials at each rescue point is \( d_1, d_2, \ldots, d_k \), and \( \sum_{m=1}^{p} c_m \geq \sum_{n=1}^{k} d_n \). Let \( C_{mn} \) denote the supply of emergency medical relief materials delivered by the \( m \) emergency logistics center to the \( n \) rescue point, \( t_{mn} \) denote the delivery time of the \( m \) emergency logistics center supplying emergency medical relief materials to the \( n \) rescue point, and \( T_n \) denote the latest time limit for the delivery of the emergency medical relief materials to the relief point \( n \).

In the case of sufficient supply of emergency medical relief materials, the decision-making goal of the configuration optimization model is mainly to meet the emergency medical relief materials requirements of each rescue point within the specified delivery time, and to plan the distribution route reasonably to minimize the total supply time of emergency medical relief materials. In order to focus on the research focus, the following assumptions are made:

1. The emergency logistics center can deliver relief materials to the rescue point multiple times, and different relief materials can be mixed for distribution.
2. The vehicles delivering emergency medical relief supplies start from the starting point and need to return to the starting point after completing the mission.
3. The strategy of "demand segmentation" is adopted for a large number of rescue points, and a combination of "full load direct delivery" and "itinerant distribution" is adopted, in accordance with the principle of full load direct delivery priority
4. The speed of the delivery vehicle changes randomly and dynamically, while the speed of the delivery helicopter is constant.

### 3.2 Objective function

#### 3.2.1 Symbol description

The variables and symbols involved in the model are explained as follows:

- \( V \): Represents the collection of delivery vehicles, and \( V = \{ v | v = 1, 2, \ldots, |V| \} \).
- \( Q_v \): Represents the capacity of the delivery vehicle \( v \), and \( Q_{vmin} \) represents the minimum capacity of the delivery vehicle.
- \( S_v \): Represents the driving speed of the delivery vehicle \( v \) under normal conditions.
- \( B \): Represents the collection of delivery helicopters, and \( B = \{ b | b = 1, 2, \ldots, |B| \} \).
$Q_b^B$: Indicates the capacity of the delivery helicopter b, and $Q_{\min}^B$ indicates the minimum capacity of the delivery helicopter.

$S_b^B$: Indicates the flight speed of the delivery helicopter b.

U: Represents the optional collection of emergency medical relief distribution points, and $U=\{u|u=1,2,\ldots,|U|\}$.

$Q_u^U$: Represents the supply of emergency medical relief materials at the distribution point u.

L: Represents an optional collection of emergency logistics centers, and $L=\{l|l=1,2,\ldots,|L|\}$.

$Q_l^L$: Represents the maximum processing capacity of the emergency logistics center l.

$Q_s$: Represents a collection of a large number of demand rescue points, whose demand is greater than $Q_{\min}^V$ or $Q_{\min}^B$.

$Q_i$: Represents the "virtual small demand rescue points" generated by a large number of demand rescue points with the help of the "demand segmentation" method, and the collection of small demand rescue points whose demand is less than $Q_{\min}^V$ or $Q_{\min}^B$.

R: The collection of all rescue points in the disaster area,

$P$: The set of all nodes, $P=U \cup L \cup R$.

$R_e$: Indicates the collection of rescue points that are not connected to any node.

$\tau_{mn}$: Represents the road connectivity between node m and node n, $\tau_{mn} \in \{0,1\}$, $\tau_{mn}=1$ indicate that the road is connected, and $\tau_{mn}=0$ indicates that the road is not connected.

$w_{mn}$: Represents the distance from node m to node n,

$T_{mn}^v$: Represents the travel time of the delivery vehicle v from node m to node n.

$T_{mn}^b$: Represents the flight time of the delivery helicopter b from node m to node n, $T_{mn}^b = w_{mn} / S_b^B$.

$T_{ul}^v$: Indicates the travel time of the delivery vehicle v from the emergency
medical relief material distribution point \( u \) to the logistics center \( l \).

\( T_{lu}^v \): Represents the travel time of the delivery vehicle \( v \) from the logistics center \( l \) to the rescue point \( n \);

\( T_{ln}^b \): Represents the travel time of the delivery helicopter \( b \) from the logistics center \( l \) to the rescue point \( n \);

\( T_l \): Indicates the total time limit for the delivery of emergency medical rescue supplies.

\( F \): Indicates the collection of emergency medical relief materials.

\( d_{nf} \): Indicates the demand for emergency medical relief materials \( f \) from the rescue point \( n \).

\( d_n \): Indicates the demand for all kinds of emergency medical relief materials at the rescue point \( n \).

The decision variables are expressed as follows:

\( a_u \): The emergency medical relief materials distribution point established at the alternative point \( u \) \((u \in U) \) is 1, otherwise it is 0.

\( z_l \): The emergency logistics center established at the alternative point \( l \) \((l \in L) \) is 1, otherwise it is 0.

\( x_{ul} \): If the emergency logistics center \( l \) is assigned to the emergency medical supplies distribution center \( u \), it is 1, otherwise it is 0.

\( y_{ln} \): If the rescue point \( n \) \((n \in R) \) is assigned to the logistics center \( l \), it is 1, otherwise it is 0.

\( g_{ln}^v \): Using a delivery vehicle \( v \) to transport emergency medical relief materials from the emergency logistics center \( l \) to the rescue point \( n \) is 1, otherwise it is 0.

\( g_{ln}^b \): Using a distribution helicopter \( b \) to transport emergency medical rescue supplies from the emergency logistics center to the rescue point \( n \) is 1, otherwise it is 0.

### 3.2.2 Design of objective function and constraint conditions

Based on the consideration of fair scheduling and multi-mode scheduling, a multi-objective LRP model with a time-constrained period and multiple types and multiple delivery methods after a disaster is constructed as follows:

\[
\min \sum_{v \in V} \sum_{l \in L} T_{ul}^v + \sum_{v \in V} \sum_{n \in R} T_{ln}^v + \sum_{b \in B} \sum_{n \in R} T_{ln}^b
\]

\[
\min \{ \max \{ \max(\sum_{v \in V} \sum_{l \in L} T_{ul}^v + \sum_{b \in B} \sum_{n \in R} g_{ln}^v \cdot T_{ln}^v), \max(\sum_{v \in V} \sum_{l \in L} T_{ul}^v + \sum_{b \in B} \sum_{n \in R} g_{ln}^b \cdot T_{ln}^b) \} \}
\]

s.t.

\[d_{nf} \leq \sum_{u \in U} Q_{uf} \cdot a_u \]

\[\sum_{l \in L} Q_{ll} \cdot z_l \leq \sum_{u \in U} Q_{lu} \cdot a_u \]
\begin{align*}
\sum_{i \in I} x_{il} & \geq a_u, \forall u \in U \\
\sum_{i \in I} d_n \leq \sum_{i \in I} Q_i^i - z_i \\
\sum_{i \in I} d_n \cdot y_{in} & \leq Q_i^i, \forall l \in L \\
\sum_{i \in I} g_{ln}^v & \geq 1, \forall v \in V \\
\sum_{i \in I} g_{ln}^b & \geq 1, \forall b \in B \\
\sum_{i \in I} d_n \cdot g_{ln}^v & \leq Q_b^b, \forall b \in B \\
\sum_{i \in I} g_{ln}^b = \sum_{i \in I} g_{ln}^b, \forall n \in L \cup R, \forall b \in B \\
\sum_{i \in I} g_{ln}^b & \leq 1 \\
\sum_{i \in I} g_{ln}^v \geq z_i \\
\sum_{n \in R} g_{ln}^b & \leq z_i, \forall l \in L, \forall b \in B \\
T_{ln}^b = T_{ln}^b + T_{mn}^b, \forall n \in R, \forall m \in L \cup R, \forall b \in B \\
T_{ln}^b & \leq T_i \\
\sum_{i \in I} d_n \cdot g_{ln}^v & \leq Q_v^v, \forall v \in V \\
\sum_{i \in I} g_{ln}^v = \sum_{i \in I} g_{ln}^v, \forall n \in L \cup R, \forall v \in V \\
\sum_{i \in I} g_{ln}^v & \leq 1 \\
\sum_{i \in I} g_{ln}^v & \geq z_i \\
\sum_{n \in R} g_{ln}^v & \leq z_i, \forall v \in V \\
T_{il}^v = T_{il}^v + T_{mn}^v, \forall n \in L, \forall m \in U \cup L, \forall v \in V \\
T_{ln}^v = T_{ln}^v + T_{mn}^v, \forall n \in R, \forall m \in L \cup R, \forall v \in V \\
T_{ln}^v & \leq T_i \\
a_u \in \{0,1\}, z_i \in \{0,1\}, x_{il} \in \{0,1\}, y_{ln} \in \{0,1\}, g_{ln}^v \in \{0,1\}, g_{ln}^b \in \{0,1\}
\end{align*}
In the above model, the objective function Eq.(1) represents the minimization of the overall dispatch time of emergency medical rescue supplies (the time from the distribution point to the emergency logistics center and the time from the emergency logistics center to the rescue point). The objective function Eq.(2) means to minimize the maximum waiting time for emergency medical relief materials to be delivered to all rescue points. The fairness of emergency medical relief materials dispatching studied in this paper is reflected by this objective function. Eq.(3) represents the total demand for multiple types of emergency medical relief materials by the rescue points. Eq.(4) represents the total supply of emergency medical relief materials at the selected distribution points must meet the total demand of the selected emergency logistics centers, Eq.(5) and Eq.(6) indicate that as long as the distribution point of emergency medical relief material is open, there must be an emergency logistics center to distribute the goods, and the emergency logistics center only distributes goods from the open distribution point. Eq.(7) means that the total demand of all selected rescue points cannot exceed the total capacity of all emergency logistics centers. Eq.(8) indicates that the maximum capacity of the emergency logistics center cannot be less than the total demand of all rescue points allocated to it. Eq.(9) and Eq.(10) indicate that each path should be connected to at least one emergency logistics center. Eq.(11) indicates that the maximum capacity of any logistics helicopter cannot be less than the total demand of all small demand rescue points allocated to it. Eq.(12) represents the path continuity constraint of the logistics helicopter, that is, if the physical helicopter enters from a node, the helicopter must leave form that node. Eq.(13) indicates that each logistics helicopter can only be allocated to one emergency logistics center at most. Eq.(14) and Eq.(15) indicate that a logistics helicopter will be assigned to an emergency logistics center whenever it is open and that the logistics helicopter can only be assigned to an emergency logistics center that is already open. Eq.(16) denotes the time for the logistics helicopter to reach the relief point. Eq.(17) denotes the time constraint for the logistics helicopter to reach the relief point. Eq.(18) denotes the maximum capacity of any transportation vehicle cannot be less than the total demand of all small demand relief points assigned to it; Eq.(19) denotes the path continuity constraint for logistics vehicles, i.e., if a logistics vehicle enters from a node, the vehicle must leave from that node. Eq.(20) indicates that each logistics vehicle can be assigned to at most one logistics center. Eq.(21) and Eq.(22) indicate that a logistics vehicle will be assigned to an emergency logistics center whenever it is open and that the logistics vehicle can only be assigned to an emergency logistics center that is open. Eq.(23) denotes the time for logistics vehicles to travel from the emergency medical relief materials distribution point to the emergency logistics center. Eq.(24) indicates the time of arrival of the logistics vehicle at the relief point. Eq.(25) denotes the time constraint for the logistics vehicle to reach the relief point. Eq. (26) denotes the 0-1 decision variable constraints.

4. Improved NSGA-II

Improved non dominated sorting genetic algorithm with elitist strategy (NSGA-II) [22] has been widely used in dealing with multi-objective optimization problems.
According to the characteristics of chromosome coding, this paper proposes a new genetic operator to solve the model.

Specific steps are as follows:

Step 1: Chromosome coding.

The length of the chromosome is determined by the total number of reserve points, each gene of the chromosome represents the decision variable $x_j$, And the sum of genes on each chromosome is the total number of materials. For example, 30 supplies are preset in the emergency system of 5 reserve points, the chromosome of any feasible solution is 8 5 4 9 4.

Step 2: Initialize the population.

According to the chromosome code of the solution individual, the initial population $P_0$ of $N$ solution individuals are randomly generated.

Step 3: Classification of population individuals.

Sorting the individuals in the population non-dominantly. The target components of any solution individuals are: $f_1(s)$ and $f_2(s)$ are the objective functions (1), (2). According to the two target components, the individuals in the population are graded layer by layer according to the Pareto dominance relationship, to be the first-level non-dominated individual set (Pareto optimal solution set) and give them a shared virtual fitness value; then, a second-level set of non-dominated individuals is formed (a set of individuals dominated only by the Pareto optimal solution set), and give them a new virtual fitness value, and so on, until all individuals are graded.

Step 4: Genetic operation.

Select operation: according to the virtual fitness value, copying the non-dominantly sorted population, and the total number of copied non-dominated individuals is $N$.

Crossover operation:

Unlike the general crossover of two chromosomes, this article only performs crossover operations on one chromosome. Given the crossover probability, randomly select the gene for crossover operation, when the selected gene location is less than half of the gene location of the chromosome, swap with the symmetrical locus respectively from the first locus to the selected locus; when the selected gene location is more than half of the chromosome gene location, swap with the symmetrical locus respectively from the selected locus to the last locus. This method ensures that the sum of each chromosome gene does not change after the operation. For example, for a chromosome with 5 gene positions, when the 2nd gene position is selected for crossover operation, the 1st and 2nd gene positions are exchanged with the 5th and 4th gene positions respectively; when the 4th gene locus is selected, the 4th and 5th gene positions are interchanged with the 2nd and 1st gene positions respectively.

Mutation operation:

Given the probability of mutation, select a gene to be mutated randomly. When the selected gene is before the penultimate gene, the selected gene is exchanged with the next one; when the selected gene is the last one, it is exchanged with the first one. This is also to ensure that the sum of each chromosome gene does not change
after the operation. For example, if the mutation of gene No. 2 occurs, it will be exchanged with gene No. 3. Through selection, crossover, and mutation operators, the progeny population \( Q_0 \) is generated.

**Step 5: The main flow of the NSGA-II algorithm**

Combine the initial population \( P_0 \) with its progeny population \( Q_0 \) to form a population \( R_0 \) with a size of \( 2N \). Then perform non-dominated sorting on the population \( R_0 \), and calculate the crowding degree for a series of non-dominated sets \( H_i \). Put \( H_1, H_2, ... \) into the new parent population \( P_1 \) until the population size exceeds \( N \) when \( H_i \) is added, sort the crowding degree of the individuals in \( H_i \), take the top \( N-P_1 \) individuals, and make the number of individuals in \( P_1 \) be \( N \). Finally, a new progeny population \( Q_1 \) is formed through genetic operations (selection, crossover, mutation) of population \( P_1 \).

Carry out step 3 to step 5 for \( Q_1 \), and repeat the above process until the set evolutionary algebra is reached. Finally, the obtained progeny population of the termination generation is the Pareto solution set.

### 5. Example simulation

#### 5.1 Parameter setting

Suppose there are five rescue points in an earthquake-stricken area. Due to differences in the distance from the rescue points to the epicenter, geological structure, building structure, population distribution, weather conditions, etc., the degree of damage and the number of affected people are also different. At a certain moment, the net demand \( c \) for relief supplies at each relief site is 950, 2000, 2500, 1650, and 2900 commodity combinations, respectively (Assume one rescue tent + two cases of mineral water + one case of instant noodles + two quilts is a combination in this paper). Suppose that the urgency of the emergency supplies for each rescue point is 0.9, 1.4, 1.1, 1.3, 1.5, there are three emergency logistics centers, and the original reserve \( b \) is 200, 500, and 300 commodity combinations. There are two material distribution points, with a supply capacity of 3900 and 4000 units respectively. According to the existing information, the material allocation system provides a total of 7,900 units, while the total demand is 10,000 units, and the total satisfaction rate is 0.79. Therefore, the equity coefficient \( e \) can be set as 0.7.

Suppose the demand limit time \( T \) of each rescue point is 20, 30, 25, 28, 31 hours respectively, the average time spent on repairing a unit journey is 3h/km, and the speeds \( v_1 \) and \( v_2 \) of various modes of transportation are respectively 60km/h and 500km/h, the transportation distance between each node is shown in Table 1 and Table 2.

| \( d_{ij} \) | \( P_1 \) | \( P_2 \) | \( P_3 \) |
|---|---|---|---|
| \( O_1 \) | 102 | 122 | 73 |
| \( O_2 \) | 93 | 151 | 52 |

| \( d_{jk} \) | \( Q_1 \) | \( Q_2 \) | \( Q_3 \) | \( Q_4 \) | \( Q_5 \) |
|---|---|---|---|---|---|
| \( P_1 \) | 113 | 74 | 132 | 91 | 82 |
| \( P_2 \) | 32 | 62 | 121 | 73 | 51 |
The road damage rate of each point is shown in table 3 and table 4:

Table 3: Road damage rate from each distribution points to each logistics center

| \( \gamma_{ij} \) | \( P_1 \) | \( P_2 \) | \( P_3 \) |
|---------------------|--------|--------|--------|
| \( O_1 \)          | 0.05   | 0.3    | 0.01   |
| \( O_2 \)          | 0.04   | 0.01   | 0.4    |

Table 4: Road damage rate from each logistics center to each relief points

| \( \gamma_{ij} \) | \( Q_1 \) | \( Q_2 \) | \( Q_3 \) | \( Q_4 \) | \( Q_5 \) |
|---------------------|--------|--------|--------|--------|--------|
| \( P_1 \)          | 0.05   | 0.02   | 0.4    | 0.5    | 0.1    |
| \( P_2 \)          | 0.3    | 0.03   | 0.4    | 0.05   | 0.08   |
| \( P_3 \)          | 0.1    | 0.5    | 0.01   | 0.6    | 0.1    |

5.2 Model solving

The model normalizes the objective function as a function of the loss of affected people to the amount of unmet demand (as shown in Eq. 27), which is a power function indicating the least total loss in the disaster relief system, and the loss is related to the urgency of the demand for emergency supplies at the affected site, the disaster index at the affected site, and the amount of unmet demand at the affected site.

\[
\min \sum_{k \in Q} \omega_k \left( \sum_{\gamma_{jk}} y_{jk}^\alpha \right) \alpha \alpha \gamma_{jk}^\alpha
\]

In this formula, \( \omega_k \) represents the urgency of the demand for the material at the \( k \)th material demand point;

\( c_k \) represents the net demand of the disaster point \( Q_k \) at a certain time;

\( y_{jk} \) represents the amount of materials distributed by the distribution center \( p_j \) to the disaster-affected point \( Q_k \).

\( \alpha \) represents the disaster index.

The model in this paper is set to \( \alpha = 2 \). In the Win 7 environment, Matlab2019b is used to execute the improved genetic algorithm proposed in this paper. Set the maximum number of iterations to 1000, and the average value of the objective function solved by running the program 20 times is 1267581. The distribution is shown in Figure 1. It can be seen that the solution obtained by this algorithm is close to the average value each time, and it has strong stability.
Take a group of optimal solutions close to the average value to obtain the optimal distribution scheme, as shown in Table 5 and Table 6:

Table 5: The amount of emergency materials distributed

|     | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
|-----|-------|-------|-------|-------|-------|
| $P_1$ | 296   | 0     | 0     | 0     | 2996  |
| $O_2$ | 279   | 3221  | 0     | 0     | 0     |
| Total | 575   | 3221  | 2996  | 0     | 0     |

Table 6: The amount of emergency supplies allocate from logistics centers to relief points

|     | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
|-----|-------|-------|-------|-------|-------|
| $P_1$ | 0     | 735   | 0     | 0     | 0     |
| $P_2$ | 0     | 682   | 0     | 1052  | 1971  |
| $P_3$ | 713   | 0     | 1887  | 0     | 697   |
| Total | 713   | 1417  | 1887  | 1052  | 2668  |

The satisfaction rate $\eta$ of each rescue point is calculated as follows:

$$\eta = (0.71 \ 0.71 \ 0.76 \ 0.70 \ 0.89)$$

From the calculation results, it can be seen that when the disaster situation cannot be completely eliminated, the satisfaction rate of each rescue point is above the fairness coefficient ($\epsilon=0.7$), and the fifth rescue point has the highest satisfaction rate among the 5 rescue points. (The urgency of the demand for materials is also the greatest), which shows that the three-level network distribution model (distribution point, emergency logistics center, rescue point) proposed in this paper can ensure the relative fairness of each rescue point on the basis of ensuring the minimum loss of the system.

### 5.3 Performance analysis of the Improved NSGA-II

To further investigate the optimization performance of the improved NSGA-II algorithm, the improved NSGA-II, NSGA and PSO algorithms were run 20 times each at different iterations and the performance was compared in terms of convergence and standard deviation:

1. Comparison of convergence curves
Figure 2 gives the mean convergence curves of the objective function values of the optimal solutions for the improved NSGA-II, NSGA and particle swarm algorithms, from which it can be seen that the improved NSGA-II algorithm converges the fastest and the calculated values basically remain around 127000 for more than 600 iterations, giving more stable results compared to the other two algorithms.

Figure 2: Comparison of the convergence curves of the improved NSGA-II with other algorithms

Table 7: Comparison of the optimization performance

| Iteration | 200 AVG | 200 STDEV | 400 AVG | 400 STDEV | 600 AVG | 600 STDEV | 800 AVG | 800 STDEV | 1000 AVG | 1000 STDEV |
|-----------|---------|-----------|---------|-----------|---------|-----------|---------|-----------|----------|------------|
| PSO       | 1757378 | 2934480   | 1534276 | 154624    | 1432184 | 81649     | 1356281 | 22451     | 1321450  | 24045      |
| NSGA      | 1637158 | 284209    | 1362333 | 174267    | 1285473 | 43859     | 1273244 | 28871     | 1283838  | 25078      |
| NSGA-II   | 1333587 | 253947    | 1319511 | 141659    | 1268207 | 35033     | 1258162 | 14708     | 1267321  | 22031      |

Combining the above results, it can be known that by establishing different learning objects for each particle in different dimensions, the search capability of the particle swarm algorithm can be improved. The improved NSGA-II is significantly better than NSGA and PSO in terms of speed of convergence, stability and accuracy of optimal solutions.

5.4 Validation of material distribution fairness model

Suppose that after a disaster event, there are n relief sites in need of certain emergency supplies, and the net demand for supplies at each relief site $P_j$ is $b_j$, and the urgency of the demand for supplies is $\omega_j$. Since the total supply of the relief site cannot fully meet all the demands at the time of the event, the total allocation will be $x_j \leq b_j$. The allocation scheme $X=\{x_j| j=1,2,\ldots,n\}$ need to be evaluated for fairness. The measurement index model was designed in this paper as follows:
(1) Calculation of equivalent demand $\gamma_j$
Considering the different degree of urgency of each relief point's demand for emergency supplies, the demand of each relief point is converted by calculating the equivalent demand, and if $\gamma_j$ denotes the equivalent demand, then $\gamma_j = b_j \cdot \omega_j$.

(2) Calculation of the fair share $\theta_j$

The equitable distribution share $\theta_j$ of the aid point represents the proportion of the equivalent demand of the aid point in the total equivalent demand of all aid points.

$$\theta_j = \frac{\gamma_j}{\sum_{k=1}^{n} \gamma_k}$$

(3) Calculation of the equivalent allocation $\gamma'_j$

The equivalent allocation of emergency supplies to a relief point is the product of the actual allocation of the affected point and the urgency of the need, i.e. $\gamma'_j = x_j \cdot \omega_j$

(4) Calculation of the actual allocation share $\rho_j$

The actual allocation share $\rho_j$ of the relief point represents the proportion of the equivalent allocation of the relief point in the total equivalent allocation of all affected points, i.e.

$$\rho_j = \frac{\gamma'_j}{\sum_{j=1}^{n} \gamma'_j}$$

(5) Calculation of the independent equity coefficient $\varphi_j$

If the actual distribution share of a rescue point is not less than the fair distribution share, the distribution scheme implements fair distribution to the affected areas, and the independent fairness coefficient $\varphi_j$ is 1, or it is unfair, the independent equity coefficient is the ratio of them, that is

$$\varphi_j = \begin{cases} 1, & \text{if } \rho_j \geq \theta_j \\ \frac{\rho_j}{\theta_j}, & \text{else} \end{cases}$$

(6) Calculation of the fairness coefficient of the system

After calculating the independent fairness coefficients for each affected point, the systematic fairness coefficient $f(\varphi_j)$ of the whole allocation scheme can be obtained, i.e.
Combining the above fairness model to evaluate the fairness of the emergency material distribution scheme based on the parameter scenario, as shown in Table 8.

Table 8: Improved NSGA-II Fairness Evaluation Form

| Relief point | Demand | Demand urgency | Allocation amount | Equivalent demand | Fair share | Equivalent distribution | Allocation share | Independent equity coefficient |
|--------------|--------|----------------|-------------------|-------------------|------------|------------------------|------------------|-------------------------------|
| 1            | 1000   | 1.0            | 723               | 1003              | 0.07       | 723                    | 0.073            | 0.9111                        |
| 2            | 2000   | 1.3            | 1427              | 2597              | 0.20       | 1856                   | 0.181            | 0.9018                        |
| 3            | 2500   | 1.1            | 1908              | 2748              | 0.21       | 2103                   | 0.218            | 0.9721                        |
| 4            | 1500   | 1.2            | 1062              | 1802              | 0.14       | 1269                   | 0.124            | 0.9011                        |
| 5            | 3000   | 1.5            | 2681              | 4502              | 0.35       | 4023                   | 0.401            | 1                             |

From Table 8, it can be seen that the distribution of independent fairness coefficients for the allocation scheme derived from the model with fairness constraints is relatively concentrated, all of them are between 0.9 and 1. Then, the fairness coefficient of the system is 0.9981 calculated according to equation (16), which indicates that the allocation scheme has good fairness.

Compared with the results obtained in Table 8, the distribution of independent fairness coefficients obtained by the general NSGA algorithm (such as Table 9) is more scattered, with values between 0.7 and 1, and the system fairness coefficient calculated according to Eq. 16 is 0.9863.

Table 9: General NSGA fairness evaluation table

| Relief point | Demand | Urgency | Allocation amount | Equivalent demand | Fairness | Equivalent distribution allocate | Allocation share | Coefficient |
|--------------|--------|---------|-------------------|-------------------|----------|----------------------------------|------------------|-------------|
| 1            | 1000   | 1.0     | 711               | 1002              | 0.079    | 713                              | 0.073            | 0.8985      |
| 2            | 2000   | 1.3     | 1803              | 2603              | 0.206    | 2342                             | 0.231            | 1           |
| 3            | 2500   | 1.1     | 1649              | 2752              | 0.217    | 1813                             | 0.178            | 0.8292      |
| 4            | 1500   | 1.2     | 861               | 1802              | 0.142    | 1031                             | 0.101            | 0.7251      |
| 5            | 3000   | 1.5     | 2771              | 4503              | 0.356    | 4159                             | 0.417            | 1           |

Compared with the results obtained by the improved NSGA-II, the value is significantly reduced. From the fairness evaluation results of the two model distribution schemes, the model obtained by the improved NSGA-II is more suitable for the distribution of emergency supplies with fair distribution requirements.

6. Conclusion

A 3-level network allocation mode with the objective of minimizing the economic cost, punishment cost and maximizing the satisfaction rate of disaster victims is proposed. According to the feature of multiple optimization parameters in the integrated model, the improved NSGA-II with a new genetic operator is designed
to obtain good individuals based on the elitist strategy. Finally, it is verified and compared with two common algorithms to obtain each target value though examples, and then process the objective parameters with the variance analysis. It can be concluded that the 3-level network allocation mode and improved NSGA-II can solve emergency relief materials allocation based on big data effectively. The next step is to design scheduling model with all feasible medical supplies allocation route to improve the practicability of the model.

**Declarations**

**Ethics approval and consent to participate**
No application.

**Consent for publication**
Not applicable.

**Availability of data and materials**
All data generated or analyzed during this study are included in this published article (and its supplementary information files).

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

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**Authors' contributions**
Ning T. analyzed and interpreted the patient data regarding the emergency material allocation. Wang J.Y. performed the Sample Average Approximation method and improved NSGA-II algorithm. Han Y.M. was a major contributor in writing the manuscript. All authors read and approved the final manuscript.

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