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Green Distribution Route Optimization of Medical Relief Supplies Based on Improved NSGA-II Algorithm under Dual-Uncertainty

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Abstract: With growing concerns about environmental issues, sustainable transport schemes are receiving more attention than ever before. Reducing pollutant emissions during vehicle driving is an essential way of achieving sustainable transport plans. To achieve sustainable transport and reduce carbon emissions, on the premise of ensuring rescue timeliness, this research proposes a multi-objective distribution route optimization model considering the minimization of transportation cost and transportation risk under dual-uncertainty constraints, providing a practical framework for determining the optimal location of rescue centers and distribution routes in emergencies using fuzzy theory. First, this paper proposes objective functions that innovatively take into account the congestion risk and accident risk during the distribution of medical supplies while introducing the carbon emission cost into the transportation cost and using the fuzzy demand for supplies and the fuzzy traffic flow on the roads as uncertainty constraints. Then, this paper designs a multi-strategy hybrid nondominated sorting genetic algorithm (MHNSGA-II) based on the original form to solve the model. MHNSGA-II adapts a two-stage real number coding method for chromosomes and optimizes the population initialization, crowding distances selection, and crossover and mutation probability calculation methods. The relevant case analysis demonstrates that, compared with the original NSGA-II, MHNSGA-II can decrease the transportation cost and transportation risk by 42.55% and 5.73%, respectively. The sensitivity analysis verifies the validity and rationality of the proposed model. The proposed framework can assist decision makers in emergency logistics rescue.

Keywords: green logistics; distribution route optimization; fuzzy constraints; multi-objective decision-making



Citation: Peng, S.; Liu, Q.; Hu, J. Green Distribution Route Optimization of Medical Relief Supplies Based on Improved NSGA-II Algorithm under Dual-Uncertainty. *Sustainability* **2023**, *15*, 11939. <https://doi.org/10.3390/su151511939>

Academic Editors: Željko Stević, Vladimir Simic and Dillip Kumar Das

Received: 17 June 2023

Revised: 24 July 2023

Accepted: 1 August 2023

Published: 3 August 2023



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1. Introduction

In recent years, public health emergencies have occurred from time to time, from SARS and Ebola to COVID-19, posing a serious threat to health. In this case, government agencies and relevant departments need to carry out abundant emergency logistics activities in a short period of time to minimize the adverse effects of these emergencies [1].

Emergency logistics is made up of multiple decision-making components, including the selection of emergency facility locations, management of emergency material storage, and transportation and distribution of emergency resources [2–4]. Among them, the distribution of emergency medical supplies is the most critical part.

Public health incidents can cause shortages of various supplies, so it is essential to provide the necessary protective and medical relief supplies to the affected people in time [5]. How to distribute emergency medical relief supplies efficiently and reasonably from rescue distribution centers to demand points using a sustainable mode of transportation is a key issue in the research of emergency logistics, which has important practical significance and value. Compared with commercial logistics, the emergency distribution of medical resources has higher requirements for timeliness, and it is necessary to consider not only

the cost but also the efficiency of the distribution process [6]. Zhao et al. [7] quantified the urgency of supply demand and road travel reliability in disaster areas and built a route optimization model with the objective of minimizing the sum of transportation time, cost, and road reliability. Petroianu et al. [8] considered the number of distribution vehicles, weather conditions, and road capacity to solve the optimization problem of emergency resource distribution routes.

With the widespread dissemination of sustainable development concepts, a large number of studies on sustainable transportation have emerged [9], such as Stević et al. [10], who developed a new integrated model of aggregators that has great significance for the sustainability of road engineering. Meanwhile, in the field of logistics and distribution, Elgharably et al. [11] studied vehicle routing problems under the sustainable goals from the perspectives of the economy, environment, and society. Alejandro et al. [12] used alternative-fuel vehicles for distribution and proposed a new approach to solve the green vehicle routing problem. At present, many scholars have introduced green and low-carbon factors into their research on general logistics distribution to achieve the goal of sustainable transportation. However, research on sustainable transportation in the distribution of emergency medical resources has not received much attention.

In this work, the study proposes a green distribution model for emergency medical resources under dual-uncertainty conditions and applies the improved NSGA-II to solve it. The paper innovatively integrates carbon emission costs and transportation risks into the proposed model, using them as part of the objective function of route optimization while considering uncertain factors in the distribution process to ultimately determine a suitable distribution route solution. Specifically, firstly, for the uncertainty of the supply demand at the demand point and the traffic flow in the distribution route, this paper establishes a multi-objective route optimization model with the objective of minimizing transportation cost and transportation risk under dual uncertainty constraints, which could also reduce the environmental impact of CO₂ emissions in the distribution process. Secondly, this paper improves the NSGA-II with a two-stage coding approach, optimizing and improving the population initialization, crowding, and cross-variance components at the same time. Finally, this paper conducts a case study based on the real situation in Shanghai, proving the effectiveness of the proposed model and improved algorithm.

To sum up, the main contributions of this paper can be illustrated as the following:

- This research presents a multi-objective green distribution model for emergency medical resources that minimizes transportation costs and transportation risks. Considering the uncertainty in the delivery process, the study innovatively introduces accident risk and congestion risk into the objective function.
- This research introduces dual-uncertainty constraints in the model; namely, the uncertainty of supply demand at the demand point and the uncertainty of traffic flow in the distribution route, which are converted into deterministic constraints with triangular fuzzy number theory.
- This research proposes a new multi-strategy hybrid improved nondominated sorting genetic algorithm (MHNSGA-II). The study improves the NSGA-II in terms of two-stage chromosome real number coding, individual insertion method for initial feasible solutions, improved crowding selection method, and adaptive cross-mutation.
- This research uses Shanghai as the case area for analysis, and the results confirm the effectiveness of the proposed model and the improved algorithm, which can provide reference for relevant decision-making.

This paper consists of six parts: Section 2 presents a literature review. Section 3 describes a multi-objective distribution route optimization model under dual uncertainty. Section 4 introduces the MHNSGA-II to solve the model. Section 5 includes a realistic case study of Shanghai and analysis of results. Section 6 summarizes the whole work and conclusions.

2. Literature Review

2.1. Sustainable Logistics Transportation

Traditional logistics approaches tend to neglect environmental sustainability in the decision-making process, while sustainable logistics achieves a balance between the economy, environment, and society by making the best use of logistics resources and technologies [13,14]. Gocmen et al. [15] designed a transportation selection model based on fuzzy risk scores with the aim of minimizing transportation costs, taking a logistics company in Turkey as the research object and providing an optimal solution for it. In order to reduce the environmental impact of logistics and transportation, Okyere et al. [16] studied multimodal transportation as the research object and established a mathematical model that integrated transportation time, transportation cost, and carbon emissions during the transportation process. Baah et al. [17] quantitatively analyzed the impact of sustainable logistics practices on the environment and finance and provided guidance for subsequent sustainability initiatives. Liu et al. [18] regarded the minimization of carbon emissions in the transportation process as the entry point of sustainable cold chain logistics and introduced various costs into the improved route optimization framework.

2.2. Uncertainties in Transportation

Nowadays, research on supply distribution route decision-making is no longer limited to conventional objectives. Scholars have introduced uncertainty as an objective or constraint condition into distribution route models and applied different algorithms to solve them [19–21]. Mohammadi et al. [22] proposed the robust optimization and the neutrosophic set method to address the uncertainty of demand, facility capacity, and transportation time in logistics. Calvet et al. [23] combined the Monte Carlo model with meta-heuristic algorithms to deal with the SMDVRP problem of limited vehicle capacity and uncertain customer demand during the distribution process. Rafael et al. [24] presented an extension of simheuristics by adding fuzzy layers to model stochasticity or fuzziness in transport problems with uncertainties such as time and demand. Considering the uncertainty of the quantity and arrival time of donations and the randomness of the number of disaster survivors in humanitarian relief, Robert et al. [25] designed the distribution strategy of distribution vehicles between the supply point and the demand point.

2.3. Application of NSGA-II in Logistics

NSGA-II and its improved forms have been widely employed in the decision-making of logistics distribution routes [26,27]. Srivastava et al. [28] improved the crossover and mutation operators based on specific problem characteristics to solve multi-objective VRPTW problems. Wang et al. [29] focused on the issue of the warehouse recycling path, introduced the resource sharing strategy, and used an improved NSGA-II to conduct a case study with Chongqing city, achieving good results. Li et al. [30] proposed a carbon-transaction-based LRIP model and redesigned the mutation operator. The results illustrated that the proposed model can effectively reduce carbon emissions. Fang et al. [31] presented a hybrid NSGA-II-based algorithm to solve the MIDL model and applied it to the actual production process of automotive manufacturing enterprises. Ghezavati et al. [32] designed a multi-echelon model and improved the NSGA. Through practical case analysis, it has been proven that the improved algorithm has more advantages in solving large problems in large models.

2.4. Multi-Criteria Decision of Distribution Route

In recent years, the application field of multi-criteria decision-making has become increasingly widespread [33], among which multi-objective decision-making is a hot issue in logistics distribution routing. Wu et al. [34] proposed a method based on symmetry and multi-criteria decision analysis for selecting the correct urban logistics distribution route. Gohari et al. [35] compared the single-objective route and the multi-criteria route solution and obtained the optimal distribution route of container transport in Malaysia under different conditions. Liu et al. [36] showed a vehicle communication-based dispatching

model for emergency supplies distribution, which calculated the shortest route for distribution vehicles while meeting the shortest delivery time and material supply requirements. Zhou et al. [37] aimed at reducing unmet demand and the selection of damaged roads, and developed a multi-cycle dynamic emergency resource dispatch distribution model. Considering various uncertain factors that may exist in the process of post-disaster distribution of supplies, Cengiz et al. [38] proposed a new method integrating multiple algorithms, aiming at reducing the distance and the number of delivery routes in the process of vehicle distribution. Sirbiladze et al. [39] simultaneously built a mathematical model of dual-fuzzy constraints and two-stage distribution route optimization, enabling distribution vehicles to find optimal transport routes despite extreme and uncertain conditions.

3. Problem Description and Model Construction

This paper investigates the distribution route optimization problem of emergency medical rescue resources. First, the study needs to determine the number and location of rescue centers; then, the delivery vehicles must provide relief supplies from the rescue centers to the demand points on the planned route in sequence according to an optimized route and finally return to the rescue centers. The distribution process is demonstrated in Figure 1.

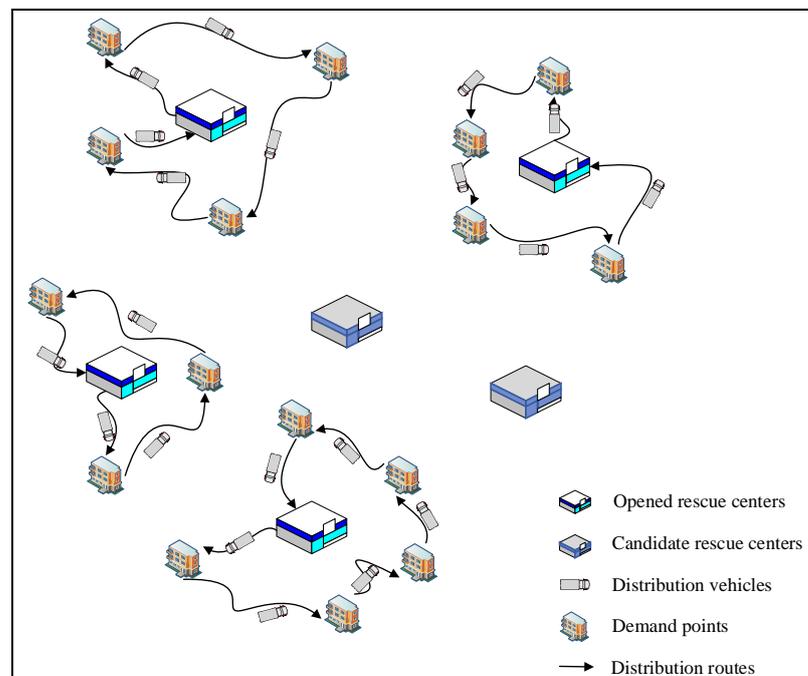


Figure 1. Distribution model of emergency medical relief materials.

After a sudden public health event, due to demand information lag and information asymmetry, it is impossible to accurately calculate the demand for materials at each demand point. In addition, there are unpredictable transportation problems in the process of dispatching medical relief supplies from rescue centers to demand points. The study sets the demand for medical relief supplies and the traffic flow during transportation as the fuzzy constraints in the model. Considering the particularity of distributing emergency medical rescue supplies, a multi-objective model with minimum transportation costs and risks was established based on the traditional distribution model. In this model, in addition to fixed vehicle costs and fuel consumption costs, low-carbon costs and late arrival penalty costs caused by congestion are also introduced into the transportation costs. At the same time, this study innovatively includes the transportation risk factors in the distribution of emergency medical relief supplies, including the risk of traffic accidents affecting road

traffic and the surrounding people and the risk of distribution time exceeding expectations due to road congestion, which affects the treatment of affected people.

To facilitate the representation of the model, the symbols involved are illustrated in Table 1.

Table 1. Symbol description.

Symbol	Description
	Parameter
I	The set of candidate rescue centers $i \in I$
J	The set of demand points $j \in J$
K	The set of distribution vehicles $k \in K$
c_k	Fixed cost of each distribution vehicle
c_0	Transport cost per unit of supply and distance
d_{mn}	Distance between node m and node n , $m, n \in I \cup J$
Q_k	Maximum capacity of each distribution vehicle
\tilde{q}_j	Fuzzy demand for medical relief supplies at demand point j , $\tilde{q}_j = (q_{1j}, q_{2j}, q_{3j})$, $q_{1j} \leq q_{2j} \leq q_{3j} \leq Q_k$
λ	Carbon tax price
μ_{mn}	Carbon emission per unit supply and distance of each distribution vehicle between node m and node n
a	Late arrival penalty factor
R_{mn}	Road traffic level between node m and node n , utilized to reflect road congestion situation
v_{mn}	Average speed of distribution vehicle traveling on uncongested roads between nodes m and n
t_{mn}^o	Minimum time of distribution vehicle traveling on uncongested roads between nodes m and n
t_{mn}	Travel time of distribution vehicle on congested roads between nodes m and n
G_{mn}	Expected maximum traffic flow of the route between nodes m and n
\tilde{f}_{mn}	Fuzzy traffic flow of the route between nodes m and n , $\tilde{f}_{mn} = (f_{1mn}, f_{2mn}, f_{3mn})$, $f_{1mn} \leq f_{2mn} \leq f_{3mn} \leq G_{mn}$
δ_1	Risk impact factor for transportation accidents
δ_2	Risk impact factor for delayed distribution of medical rescue supplies
β_{mn}	Probability of accidents occurring in the route between nodes m and n
S_{mn}	Area affected by accidents in the route between nodes m and n
r	The radius of the area affected by the accident
	Decision Variables
X_{mn}^k	If vehicle k travels from node m to node n , the value is 1; otherwise, it is 0. $m, n \in I \cup J$
Y_i^k	If vehicle k is assigned of the rescue center i , the value is 1; otherwise, it is 0. $m, n \in I \cup J$
Z_i	If the rescue center i is opened, the value is 1, otherwise it is 0.

The assumptions of the model are as follows:

- The number and location of candidate rescue centers are known.
- The number and location of medical rescue supply demand points are known.
- Each demand point can be served by only one rescue center and one vehicle.
- The route of distribution vehicles must start and end at the same rescue center.
- The total quantity of medical supplies for the rescue centers is able to meet total demand.
- The medical supplies in this paper mainly include medicines and epidemic prevention supplies.

3.1. Dual-Uncertainty Constraints

3.1.1. Constraint of Uncertain Supplies Demand

After an emergency event, the rescue center needs to provide the service of distributing emergency medical supplies to demand points. However, due to uncertainty and lag, the demand for medical relief supplies at each demand point is uncertain.

This study uses \tilde{q}_j to denote the fuzzy demand for supplies of each demand point. Due to the limited capacity of distribution vehicles, α_1 is defined as the reliability that the

supply demand of each demand point does not exceed the maximum capacity Q_k of the distribution vehicle. Therefore, the constraint equation is expressed as:

$$Cr \left(\sum_{j \in J} \sum_{m \in IUJ} \sum_{n \in IUJ} \tilde{q}_j X_{mn}^k \leq Q_k \right) \geq \alpha_1 \quad (1)$$

3.1.2. Constraint of Uncertain Traffic Flow

During the distribution process of medical rescue supplies, if the traffic flow of the distribution route is too high, it will lead to the possibility of vehicle congestion and the increased probability of traffic accidents. Congestion and traffic accidents can affect the normal movement of vehicles on the road and prolong the transportation time of medical supplies. Considering distribution efficiency, \tilde{f}_{mn} is used to indicate fuzzy traffic flow on distribution routes and formulate α_2 as the reliability that the traffic flow of each distribution route mn does not exceed the expected maximum traffic flow G_{mn} . The constraint equation is denoted as:

$$Cr \left(\sum_{m \in IUJ} \sum_{n \in IUJ} \tilde{f}_{mn} X_{mn}^k \leq G_{mn} \right) \geq \alpha_2 \quad (2)$$

3.2. Multi-Objective Distribution Route Optimization Model

3.2.1. Transportation Cost

In the proposed model, the transportation costs in sustainable green distribution are mainly composed of vehicle fixed cost, fuel cost, carbon emission cost, and time cost.

Vehicle fixed cost mainly consists of purchase, maintenance, and depreciation costs, etc. and is usually calculated at constant values. Fuel cost is mainly related to the distance and the number of supplies transported. Carbon emission cost is calculated based on the carbon tax policy, expressed by multiplying the carbon tax price by the total amount of carbon emissions, where the total carbon emissions are equal to the total fuel consumption multiplied by the CO₂ emission factor. Time cost is used to describe the penalty caused by the vehicle distribution time exceeding the expected time due to road congestion, where the minimum time a vehicle can travel with an unblocked road is taken as the expected time. In order to quantitatively describe the driving situation of vehicles in congested road conditions, combining "Chinese road capacity guidelines" and road traffic flow characteristics, this paper sets R as "the road traffic flow evaluation coefficient" and divides road traffic conditions into five levels: $0.00 \leq R \leq 0.30$ means unblocked state; $0.30 < R \leq 0.60$ is a slightly congested state; $0.60 < R \leq 0.75$ is a somewhat congested state; $0.75 < R \leq 0.90$ is a more congested state; $0.90 < R \leq 1.00$ means a congested state; and $R > 1.00$ is heavy congestion. Based on this, the study establishes a vehicle travel time model function:

$$\begin{cases} t_{mn} = \frac{2}{3} t_{mn}^0 (1 + R^{1.88+7R^3}) \\ t_{mn}^0 = \frac{d_{mn}}{v_{mn}} \end{cases} \quad (3)$$

The total transportation cost during the distribution supplies process can be expressed as:

$$\begin{aligned} \min C = & \sum_{i \in I} \sum_{k \in K} c_k Y_i^k + \sum_{i \in I} \sum_{j \in J} \sum_{m, n \in IUJ} \sum_{k \in K} c_0 \tilde{q}_j d_{mn} X_{mn}^k Y_i^k Z_i \\ & + \sum_{i \in I} \sum_{j \in J} \sum_{m, n \in IUJ} \sum_{k \in K} \lambda \tilde{q}_j \mu_{mn} d_{mn} X_{mn}^k Y_i^k Z_i + \sum_{m \in IUJ} \sum_{n \in IUJ} \sum_{k \in K} a (t_{mn} - t_{mn}^0) X_{mn}^k \end{aligned} \quad (4)$$

3.2.2. Transportation Risk

The transportation risk in the green distribution process of medical relief supplies mainly includes accident risk and congestion risk.

Accident risk is related to the probability of an accident, traffic flow, and the area affected by the accident, which will affect the material distribution process if a traffic

accident occurs, assuming that when an accident occurs, the area within the radius of r will be affected. Therefore, the area S_{mn} affected by the accident is defined as:

$$S_{mn} = 2rd_{mn} + \pi r^2 \quad (5)$$

The congestion risk has an impact on distribution time and rescue efficiency, as road congestion will lead to distribution time exceeding expectations, thereby delaying the treatment of affected populations. This research combines accident risk and congestion risk as potential risks in transportation, which can be computed as:

$$\begin{aligned} \min E &= \sum_{m \in I \cup J} \sum_{n \in I \cup J} \sum_{k \in K} \delta_1 \beta_{mn} \tilde{f}_{mn} S_{mn} X_{mn}^k + \sum_{j \in J} \sum_{m \in I \cup J} \sum_{n \in I \cup J} \sum_{k \in K} \delta_2 (t_{mn} - t_{mn}^0) \tilde{q}_j X_{mn}^k \\ &= \sum_{m \in I \cup J} \sum_{n \in I \cup J} \sum_{k \in K} \delta_1 \beta_{mn} \tilde{f}_{mn} S_{mn} X_{mn}^k + \sum_{j \in J} \sum_{m \in I \cup J} \sum_{n \in I \cup J} \sum_{k \in K} (1 - \delta_1) (t_{mn} - t_{mn}^0) \tilde{q}_j X_{mn}^k \end{aligned} \quad (6)$$

where $\delta_1 + \delta_2 = 1$.

3.2.3. Multi-Objective Model

A multi-objective distribution route optimization model has been formulated using the above variables, uncertainty constraints and parameters.

$$f_1(x) = \min C \quad (7)$$

$$f_2(x) = \min E \quad (8)$$

s.t.

$$Cr \left(\sum_{j \in J} \sum_{m \in I \cup J} \sum_{n \in I \cup J} \tilde{q}_j X_{mn}^k \leq Q_k \right) \geq \alpha_1, \forall j \in J, \forall k \in K \quad (9)$$

$$Cr \left(\sum_{m \in I \cup J} \sum_{n \in I \cup J} \tilde{f}_{mn} X_{mn}^k \leq G_{mn} \right) \geq \alpha_2, \forall m, n \in I \cup J \quad (10)$$

$$\sum_{i \in I} Y_i^k \leq Z_i, \forall k \in K \quad (11)$$

$$\sum_{j \in J} X_{ij}^k = Y_i^k, \forall i \in I, \forall k \in K \quad (12)$$

$$\sum_{i \in I} \sum_{k \in K} X_{ij}^k \leq 1, \forall j \in J \quad (13)$$

$$\sum_{i \in I} \sum_{j \in J} X_{ij}^k \leq 1, \forall k \in K \quad (14)$$

$$\sum_{m \in E} \sum_{n \in E} X_{mn}^k \leq |E| - 1, \forall E \subseteq J, \forall k \in K \quad (15)$$

$$\sum_{m \in I \cup J} X_{mj}^k - \sum_{n \in I \cup J} X_{jn}^k = 0, \forall j \in J, \forall k \in K \quad (16)$$

$$\sum_{k \in K} X_{in}^k = 0, \forall i \in I, \forall n \in I \quad (17)$$

$$\sum_{m \in I} \sum_{n \in J} X_{mn}^k = 1, \forall k \in K \quad (18)$$

$$\sum_{m \in J} \sum_{n \in I} X_{mn}^k = 1, \forall k \in K \quad (19)$$

$$Q_k \geq \sum_{j \in J} \tilde{q}_j X_{mn}^k, \forall m, n \in I \cup J, \forall k \in K \quad (20)$$

$$X_{mn}^k \in \{0, 1\}, \forall m, n \in I \cup J, \forall k \in K \quad (21)$$

$$Y_i^k \in \{0, 1\}, \forall i \in I, \forall k \in K \quad (22)$$

$$Z_i \in \{0, 1\}, \forall i \in I \quad (23)$$

Objective function Equation (7) minimizes the total fixed and variable transportation costs. Objective function Equation (8) measures the total risks throughout the whole process. Equation (9) represents the constraint of demand points on the fuzzy demand for medical rescue supplies. Equation (10) requires the constraint of the path between two nodes for road fuzzy traffic flow. Equation (11) indicates that there are no vehicles driving out of an unopened rescue center. Equation (12) ensures that there will be a distribution vehicle to deliver medical relief supplies to the opened rescue center. Equation (13) shows that any demand point accepts only one rescue center providing rescue supplies. Equation (14) indicates that each distribution vehicle will provide service for only one rescue center. Equation (15) ensures the avoidance of distribution sub-loops between the demand points in the distribution process; E is all the affected demand points that the vehicle passes through in a certain route. Equation (16) requires that the vehicle must exit from and drive out from the same node. Equation (17) indicates avoiding routes between open rescue centers. Equations (18) and (19) show that the start of the route is the rescue center. Equation (20) requires that the number of relief supplies carried by each distribution vehicle must not exceed its maximum carrying capacity. Equations (21)–(23) represent constraints on decision variables.

3.3. Defuzzification of Fuzzy Chance Constraints

Triangular fuzzy number is a concept proposed by Zadeh [40] in 1965, which is used to solve problems under uncertain conditions.

Definition 1. If U is a given theoretical domain, and for any $x \in U$, there exists a number $0 \leq \zeta(x) \leq 1$ corresponding to it, then $\zeta(x)$ is called the subordination of x to U , and ζ is the subordination function of x , which is the fuzzy number.

If $\tilde{A} = (a_1, a_2, a_3)$ is a triangular fuzzy number, $a_1 \leq a_2 \leq a_3$, a_1 and a_3 are the upper and lower bounds of this triangular fuzzy number, respectively, and a_2 is the median, then its subordinate function $\zeta_{\tilde{A}}(x)$ can be expressed as [41]:

$$\zeta_{\tilde{A}}(x) = \begin{cases} 0, & x < a_1 \\ \frac{x-a_1}{a_2-a_1}, & a_1 \leq x \leq a_2 \\ \frac{a_3-x}{a_3-a_2}, & a_2 \leq x \leq a_3 \\ 0, & x \geq a_3 \end{cases} \quad (24)$$

Definition 2. Based on the fuzzy credibility theory, the fuzzy chance constraint can be converted into a deterministic constraint, that is, the fuzzy constraint can be defuzzification, so that the probability of the fuzzy chance constraint is not less than the specified fuzzy quantity preference value [42,43].

If $\tilde{A} = (a_1, a_2, a_3)$ is a triangular fuzzy number and B is the preference value of the given determined fuzzy quantity, according to the fuzzy credibility theory, the defuzzification can be expressed as:

$$Cr(\tilde{A} \leq B) = \begin{cases} 0, & B \leq a_1 \\ \frac{B-a_1}{2 \times (a_2-a_1)}, & a_1 \leq B \leq a_2 \\ \frac{B+a_3-2a_2}{2 \times (a_3-a_2)}, & a_2 \leq B \leq a_3 \\ 1, & a_3 \leq B \end{cases} \quad (25)$$

According to the fuzzy credibility theory, the fuzzy demand and fuzzy traffic flow in this paper are defuzzified and transformed into a certain form. Because the demand \tilde{q}_j is a triangular fuzzy number, according to fuzzy number theory, $\tilde{q}_j X_{mn}^k$ is also a triangular fuzzy number; so, let $\tilde{U}_j = \sum_{j \in J} \sum_{m \in I \cup J} \sum_{n \in I \cup J} \tilde{q}_j X_{mn}^k$, therefore $\tilde{U}_j = (\sum_{j \in J} \sum_{m \in I \cup J} \sum_{n \in I \cup J} q_{1j} X_{mn}^k, \sum_{j \in J} \sum_{m \in I \cup J} \sum_{n \in I \cup J} q_{2j} X_{mn}^k, \sum_{j \in J} \sum_{m \in I \cup J} \sum_{n \in I \cup J} q_{3j} X_{mn}^k) = (U_{1j}, U_{2j}, U_{3j})$.

According to Definition 2, the fuzzy demand can be expressed as:

$$Cr(\tilde{U}_j \leq Q_k) = \begin{cases} 0, & Q_k \leq U_{1j} \\ \frac{Q_k-U_{1j}}{2 \times (U_{2j}-U_{1j})}, & U_{1j} \leq Q_k \leq U_{2j} \\ \frac{Q_k+U_{3j}-2U_{2j}}{2 \times (U_{3j}-U_{2j})}, & U_{2j} \leq Q_k \leq U_{3j} \\ 1, & U_{3j} \leq Q_k \end{cases} \quad (26)$$

Similarly, for the road fuzzy traffic flow in the distribution path of medical relief supplies $\tilde{f}_{mn}, \tilde{f}_{mn} X_{mn}^k$ is also a triangular fuzzy number, making $\tilde{V}_{mn} = \sum_{m \in I \cup J} \sum_{n \in I \cup J} \tilde{f}_{mn} X_{mn}^k$, so $\tilde{V}_{mn} = (\sum_{m \in I \cup J} \sum_{n \in I \cup J} f_{1mn} X_{mn}^k, \sum_{m \in I \cup J} \sum_{n \in I \cup J} f_{2mn} X_{mn}^k, \sum_{m \in I \cup J} \sum_{n \in I \cup J} f_{3mn} X_{mn}^k) = (V_{1mn}, V_{2mn}, V_{3mn})$; the road fuzzy traffic flow can be expressed as:

$$Cr(\tilde{V}_{mn} \leq G_{mn}) = \begin{cases} 0, & G_{mn} \leq V_{1mn} \\ \frac{G_{mn}-V_{1mn}}{2 \times (V_{2mn}-V_{1mn})}, & V_{1mn} \leq G_{mn} \leq V_{2mn} \\ \frac{G_{mn}+V_{3mn}-2V_{2mn}}{2 \times (V_{3mn}-V_{2mn})}, & V_{2mn} \leq G_{mn} \leq V_{3mn} \\ 1, & V_{3mn} \leq G_{mn} \end{cases} \quad (27)$$

4. Improved NSGA-II

The multi-objective distribution route optimization problem is characterized by multiple constraints and high complexity and is a typical NP-hard problem. The NSGA-II proposed by Kalyanmoy et al. [26] is one of the most widely used for solving this problem. NSGA-II incorporates the elite selection strategy and fast, nondominated sorting on the basis of the original genetic algorithm, enhancing the optimization effect. However, there are still shortcomings, such as premature convergence and falling into local optima solution. Therefore, this study designs a new multi-strategy hybrid improved nondominated sorting genetic algorithm (MHNSGA-II) to solve the model above. The MHNSGA-II flow is shown in Figure 2.

MHNSGA-II runs as follows: first, a two-stage chromosome real number coding strategy and individual insertion method are used to randomly generate chromosomes as initial populations; second, after nondominated sorting and selection operations, using improved adaptive crossover and mutation probability to generate offspring populations, the two populations are merged to form a new parent population. Then, through rapid nondominated sorting, the individuals with higher Pareto ranks are calculated for the crowding distance proportion with a "roulette wheel" method, selecting individuals with a large proportion to form new parent populations. Finally, the above process is used to generate new offspring populations, which are merged with the new parent populations, and the above operation is repeated until the maximum number of evolutionary generations is satisfied, the optimal solution set is output, and the algorithm run ends.

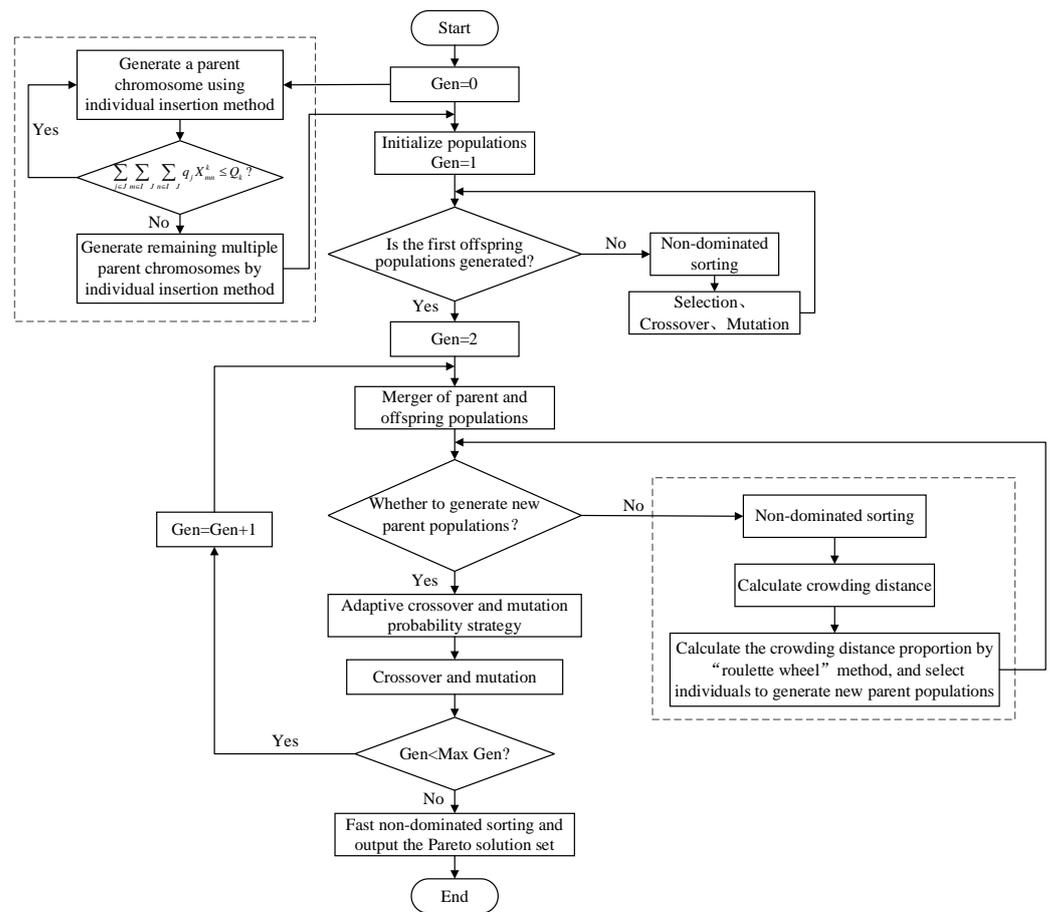


Figure 2. Flow chart of MHNSGA-II.

4.1. Chromosome Coding

This paper adapts a two-stage chromosome real number coding strategy: the first part represents the rescue center corresponding to each demand point, and the second part represents the delivery sequence of the demand point in the vehicle distribution process. The coding method is shown in Figure 3. Assuming that there are seven demand points and three medical rescue centers, and the demand for medical supplies at each demand point does not exceed the maximum carrying capacity of the distribution vehicle, it can be seen that rescue center 1 provides supplies for demand points 2 and 5, rescue center 2 provides supplies for demand points 3, 4, and 7, and rescue center 3 provides supplies for demand points 1 and 6. According to the distribution order of demand points, the distribution routes of the three rescue centers are as follows:

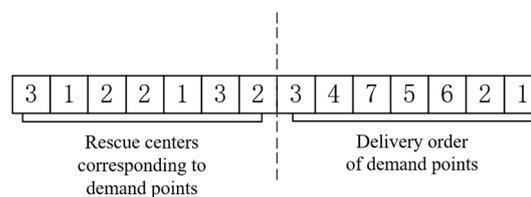


Figure 3. Chromosome coding mode.

Center 1 → 2 → 5 → Center 1, Center 2 → 7 → 4 → 3 → Center 2, Center 3 → 6 → 1 → Center 3.

In the process of allocating vehicles, due to the constraints of the maximum carrying capacity of the distribution vehicles, if the fuzzy total demand of a certain demand point exceeds the distribution margin of the vehicles already on the distribution task, other vehicles from that rescue center will carry out the distribution until all demand points have vehicles to provide them with distribution services.

4.2. Improvement of Population Initialization

The performance of NSGA-II depends to some extent on the quality of the population initialization. This paper improves the process of population initialization and uses the individual insertion method to obtain initial solutions. That is, under the constraint of fuzzy demand, demand points are inserted one by one in a distribution path until the total demand of distribution exceeds the maximum carrying capacity of the vehicle, and then no more demand points are inserted, at which time an initial feasible solution is generated. The specific steps are as follows:

Step 1: Randomly select a demand point j and put it in the vehicle distribution route. At this time, the number of vehicles used is $k = 1$, and the vehicle load is \tilde{q}_j .

Step 2: Continue to randomly select from the remaining demand points, placing them after the demand point j . Add a new distribution vehicle, insert the remaining demand points into the delivery route of the vehicle in sequence, calculate whether the loading capacity of vehicle 1 meets the maximum carrying capacity, and so on, until all the demand in the distribution route exceeds the maximum carrying capacity.

Step 3: Add a new distribution vehicle, and insert the remaining demand points into the distribution route of the vehicle in sequence.

Step 4: Follow steps 2 and 3 in a loop, and after all demand points have been assigned, obtain the matrix with the number of vehicles as k . Randomly assign the initial route to each medical rescue center to obtain the initial population.

4.3. Improvement of Crowding Distances Selection

In NSGA-II, the use of “crowding” is proposed to maintain the diversity of the population. For individuals in the same noninferior class, it is necessary to compare the degree of congestion between the two and select the individual with a higher degree of congestion to enter the next step, as shown in Figure 4. This paper assumes that L_i is the crowding distance of feasible solution i ; y_1^{i-1} and y_1^{i+1} are, respectively, the values of the former and latter solutions of the feasible solution i on the function y_1 ; f_1^{\max} and f_1^{\min} are the maximum and minimum values of the function y_1 ; and the formula for calculating the crowding distance is:

$$L_i = \frac{|y_1^{i-1} - y_1^{i+1}|}{f_1^{\max} - f_1^{\min}} \quad (28)$$

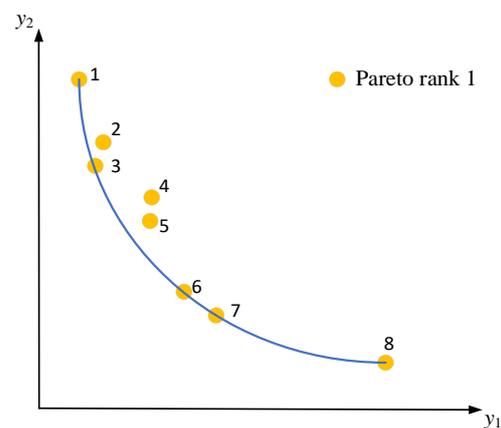


Figure 4. Schematic diagram of individual selection at Pareto rank 1.

In Figure 4, if decision makers aim to select five of the eight individuals in Pareto rank 1 for the next operation, compared with individuals 3 and 6, individuals 2, 4, and 5 are closer to the Pareto frontier. However, due to the small crowding distance of these individuals, they are excluded from the selection process, resulting in the quality degradation of the final solution. Thus, the research improves this strategy: in the process of selecting new populations, individuals of the same Pareto rank are no longer chosen according to the order of crowding, but via roulette wheel. This means that the greater the crowding of individuals, the greater the probability of being selected. Specifically, the following steps are used to calculate the q_i :

Step 1: Assuming a population size of N , calculate the proportion of crowding distance for each individual as the probability of it being selected,

$$p_i = \frac{L_i}{\sum_{j=1}^N L_j} \quad (29)$$

Step 2: Calculate the cumulative probability of individuals,

$$q_i = \sum_{j=1}^i L_j \quad (30)$$

Step 3: Randomly generated $\gamma \in [0, 1]$, if $q_1 < \gamma$, choose individual 1 for the subsequent parts; if $q_{i-1} \leq \gamma \leq q_i$, choose individual i .

4.4. Adaptive Crossover and Mutation Probability

In the process of individual genetic manipulation, the magnitude of the crossover and variation probabilities (p_c and p_m) plays a key role in the convergence speed of the algorithm. For the original NSGA-II, inappropriate crossover and mutation probability values greatly affect the diversity of the population and the search speed of the algorithm, resulting in premature convergence of the solution process.

To address this problem, the research introduces adaptive crossover and mutation probability strategy, so that both of them change automatically with the population fitness. The crossover probabilities and mutation probabilities are calculated as follows:

$$\begin{cases} P_c = \text{mean}(P_{ci}) \\ P_m = \text{mean}(P_{mi}) \end{cases} \quad (31)$$

$$P_{ci} = \begin{cases} \frac{P_{c3}(\bar{f}(i) - f'(i)) + P_{c2}(f'(i) - f(i)_{\min})}{\bar{f}(i) - f(i)_{\min}}, & f'(i) < \bar{f}(i) \\ \frac{P_{c2}(f(i)_{\max} - f'(i)) + P_{c1}(f'(i) - \bar{f}(i))}{f(i)_{\max} - \bar{f}(i)}, & f'(i) \geq \bar{f}(i) \end{cases} \quad (32)$$

$$P_{mi} = \begin{cases} \frac{P_{m3}(\bar{f}(i) - f(i)) + P_{m2}(f(i) - f(i)_{\min})}{\bar{f}(i) - f(i)_{\min}}, & f(i) < \bar{f}(i) \\ \frac{P_{m2}(f(i)_{\max} - f(i)) + P_{m1}(f(i) - \bar{f}(i))}{f(i)_{\max} - \bar{f}(i)}, & f(i) \geq \bar{f}(i) \end{cases}$$

where P_{ci} and P_{mi} are the crossover and mutation probabilities of the i -th objective function; P_c and P_m are the average values of P_{ci} and P_{mi} ; $f(i)_{\max}$, $f(i)_{\min}$, and $\bar{f}(i)$ are the maximum, minimum, and average values of the objective function, respectively; $f'(i)$ is the larger value of fitness of the two individuals to be crossed; and $f(i)$ is the fitness value of the individuals to be mutated. And $0 < P_{c1} < P_{c2} < P_{c3}, 0 < P_{m1} < P_{m2} < P_{m3}$ [44].

5. Case Study

This paper takes a case study about the real situation of Shanghai; therefore, the locations of candidate rescue centers and demand points are based on the administrative districts of Shanghai. According to the locations of the tertiary hospitals in Shanghai, the study used the straight-line connection method and the entropy weight method (EWM) to determine the candidate rescue centers (numbered 1–10). Meanwhile, combined with the merger and division of the streets in each administrative area, finally 55 demand points (numbered 11–65) were selected.

5.1. Data Acquisition and Parameter Setting

According to the objective function model established above, the study collected the required data, and the relevant information of the candidate rescue centers and demand points are displayed in Tables 2 and 3. The medical supplies involved in this article mainly include essential daily medicines (such as anti-inflammatory drugs and painkillers), medical disinfectants (such as medical alcohol, chlorine dioxide, and sodium hypochlorite), improvised medical equipment (such as disposable infusion sets, sphygmomanometers, and oxygen cylinders), and so on. Considering the actual situation of emergencies, according to the population density data of each street, the study fuzzed the demand quantity at each demand point. For example, the fuzzy demand of No. 10 demand point

is (104,137,170), which means that the minimum demand for supplies at this demand point is 104, the maximum demand is 170, and the middle part is the average of the two.

Table 2. Candidate rescue center location.

No.	Longitude	Latitude	No.	Longitude	Latitude
1	121.287859	31.063992	6	121.467594	31.216567
2	121.348194	31.116493	7	121.452872	31.212319
3	121.383997	31.078014	8	121.522425	31.295325
4	121.444263	31.194638	9	121.392983	31.247921
5	121.459204	31.223377	10	121.462506	31.246864

Table 3. Demand point location and material fuzzy demand.

No.	Longitude	Latitude	Fuzzy Demand
11	121.483268	31.238749	(104,137,170)
12	121.489980	31.224447	(91,122.5,154)
13	121.487475	31.209581	(93,125.5,158)
...
63	121.517698	31.203494	(110,130.5,151)
64	121.539659	31.176098	(101,131.5,162)
65	121.619286	31.082794	(97,126,155)

The parameters are set as follows: $c_k = 200$; $c_0 = 0.5$; $Q_k = 1500$; $\lambda = 0.2$; $\mu_{mn} = 0.3$; $a = 10$; H_{mn} is a random number in $[0.1, 0.3]$; v_{mn} is a random number in $[50, 60]$; $G_{mn} = 2000$; and fuzzy traffic flow between routes is $\tilde{f}_{mn} = (f_{1mn}, f_{2mn}, f_{3mn})$, where f_{1mn} takes random values between $[150, 200]$, f_{3mn} takes random values between $[350, 400]$, and f_{2mn} is the average of both. Both δ_1 and δ_2 are 0.5. By referring to historical data, β_{mn} is taken as a random number between $[0.3\%, 0.5\%]$, and $r = 5$.

5.2. Results Analysis

This paper adopted MatlabR2018a to solve the model. The parameters were set to PopSize = 200, MaxIteration = 500, and the initial values of p_c and p_m were 0.9 and 0.1, respectively [45,46]. Each opened rescue center had up to three vehicles for distribution at the same time. The resulting Pareto optimal solution is displayed in Figure 5.

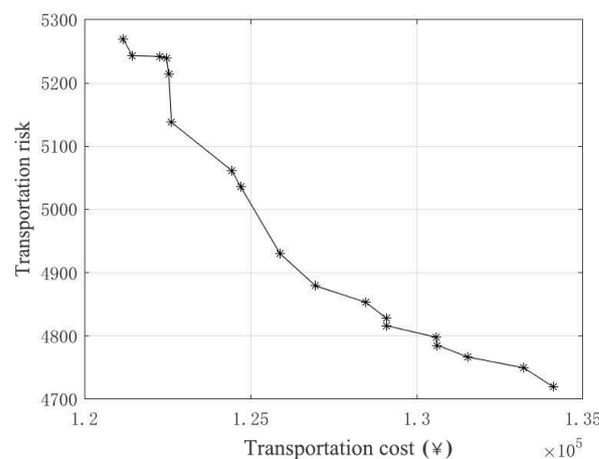


Figure 5. Pareto optimal solution of objective function under MHNSGA-II.

Eighteen Pareto solutions were obtained with MHNSGA-II. There is a conflict between the two objective functions, and they cannot reach the minimum at the same time, which demonstrates that there is a phenomenon of “trade off” between transportation costs and transportation risks. The distribution of the optimal solutions in the Pareto frontier was relatively uniform. When the minimum value of transportation cost reached 121,172.85, the value of transportation risk was 5268.81. Based on the Pareto principle, the analysis shows that transport risk “E” is minimized when transport

cost “C” is maximized, and when the transportation risk “E” is maximized, the transportation cost “C” is minimized, which means there is a “trade off” phenomenon between the two. Therefore, decision makers can make different choices according to the urgency of the situation when making relevant decisions. For example, in an emergency or major situation, medical supplies should be delivered as soon as possible, so they can choose a solution with lower risk and higher cost to ensure the timeliness of the supplies. Conversely, they can choose a less costly solution.

In this Pareto optimal solution set, a total of 8 emergency medical rescue centers served 55 demand points, and the remaining 2 were ignored; the set of generated optimal distribution routes is shown in Table 4 and Figure 6.

Table 4. Vehicle distribution routes set based on MHNSGA-II.

Rescue Center No.	Number of Distribution Vehicles	Distribution Route	Rescue Center No.	Number of Distribution Vehicles	Distribution Route
1	3	1-57-1 1-58-56-54-1 1-55-52-1	5	3	5-24-25-5 5-12-23-17-22-36-35-5 5-47-5
2	1	2-53-2	6	3	6-19-16-31-34-6 6-18-39-38-15-6 6-20-13-42-6
3	3	3-59-61-3 3-41-63-62-3 3-60-64-3	7	3	7-14-37-21-7 7-11-43-7 7-40-7
4	3	4-65-4 4-30-27-26-4 4-29-28-32-4	9	3	9-51-44-46-9 9-49-50-48-9 9-33-45-9

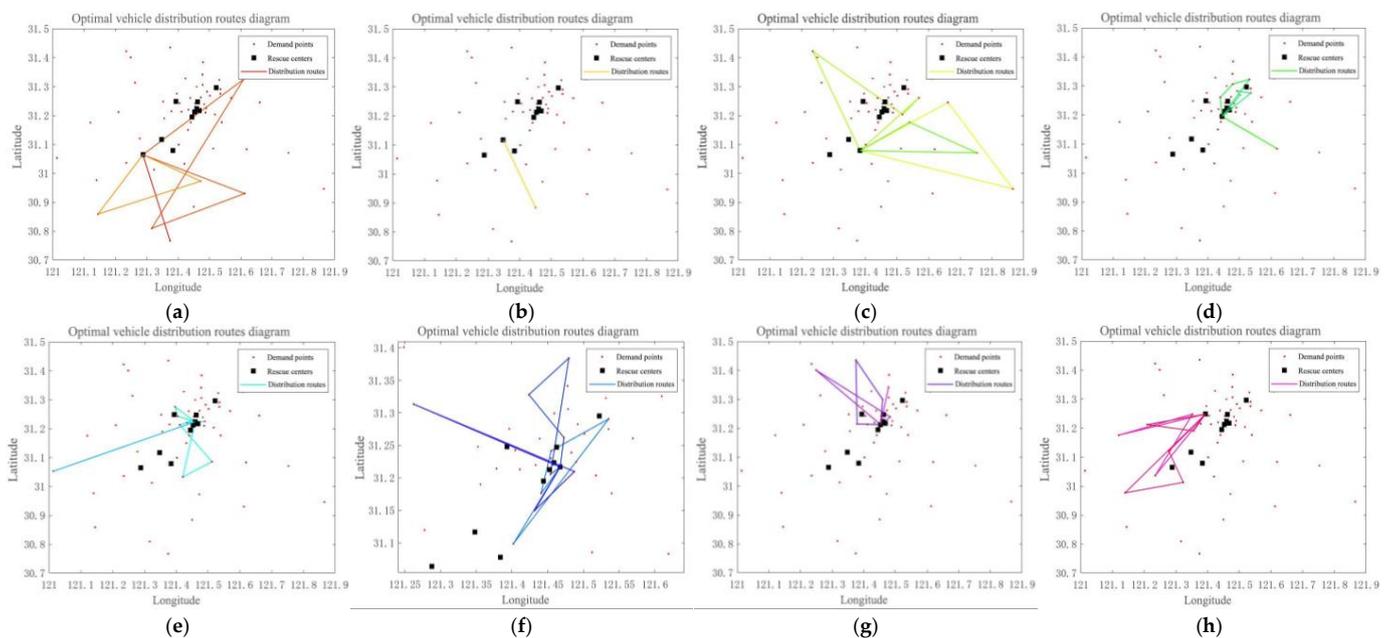


Figure 6. Vehicle distribution routes diagram based on MHNSGA-II. (a) Distribution routes of rescue center No. 1. (b) Distribution routes of rescue center No. 2. (c) Distribution routes of rescue center No. 3. (d) Distribution routes of rescue center No. 4. (e) Distribution routes of rescue center No. 5. (f) Distribution routes of rescue center No. 6. (g) Distribution routes of rescue center No. 7. (h) Distribution routes of rescue center No. 9.

Under the constraint of uncertain demand, most rescue centers prioritize the distribution of closer and more concentrated demand points, and then consider providing services for demand points that are farther away, thus effectively shortening the total transportation distance to reduce transportation costs and carbon emissions. Additionally, with a reduction in the number of rescue centers, it is possible to meet traffic flow constraints, which could decrease transportation risk and achieve multi-objective optimization.

Hence, depending on the urgency of the situation and the degree of road congestion at that time, decision makers can decrease the risk of delayed distribution of medical supplies or reduce the transportation cost by adjusting relevant parameter values. Under the premise of being able to meet the needs of the demand points and various constraints, green and efficient distribution of medical supplies can be achieved by changing the number of rescue centers opened and vehicles used, etc., and by selecting the closest road for distribution according to the route diagrams.

5.3. Sensitivity Analysis

5.3.1. Sensitivity Analysis of Vehicle Usage

To explore the specific effect of total vehicle usage on the objective function, the maximum number of vehicles that provide service at the same time in each rescue center was set to two, three, four, and five. Using the case results in Section 5.2 as the control group, the results were compared with respect to the total vehicle usage, transportation cost, transportation risk, degree of variation, and algorithm running time, as shown in Table 5. In Figure 7, the effects of the different numbers of vehicles used on the two objective functions can be seen more clearly and intuitively.

Table 5. Comparison of objective functions under different distribution vehicles.

Maximum Number of Vehicles in Each Rescue Center	Total Number of Vehicles	Transportation Cost		Transportation Risk		Algorithm Running Time
		Value	Variation	Value	Variation	
2	16	132,865.12	9.65%	4968.26	−5.70%	78 s
3	22	121,172.85	—	5268.81	—	82 s
4	31	113,076.32	−6.68%	5735.50	8.86%	89 s
5	34	116,140.54	−4.15%	5896.14	11.91%	88 s

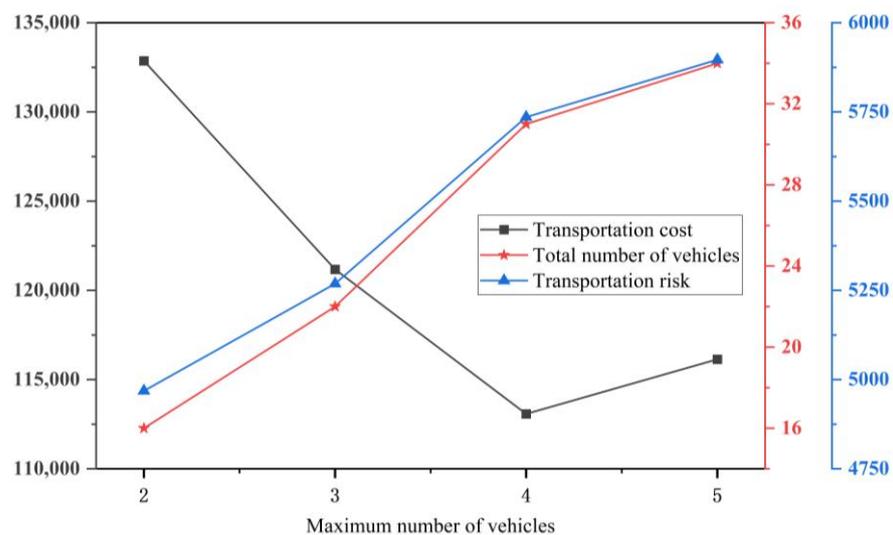


Figure 7. The impact of different numbers of vehicles used on the objective functions.

The analysis shows that: (a) The fewer vehicles used, the higher the transportation cost and the lower the transportation risk. Due to the increase in the number of vehicles, the distribution task of each vehicle is reduced, but the increase in the total distribution routes raises the risk in transportation. (b) When the maximum number of vehicles in a single rescue center is changed, the transportation cost, total vehicle usage, transportation risk, and algorithm running time all change accordingly, which means that the number of vehicles plays a role in the objective function.

5.3.2. Sensitivity Analysis of Risk Impact Factors

The transportation risk comprises accident risk and congestion risk, and the sum of the weights of the two is constant at 1. To explore the effects of the two risks on the transportation situation, the risk impact factors of the two were set to 0.3 and 0.7, 0.4 and 0.6, 0.6 and 0.4, and 0.7 and 0.3. The results of the cases in Section 5.2 were used as a control group (the bold line) to compare the results regarding transportation cost, transportation risk, degree of variation, and algorithm run time, as shown in Table 6. In Figure 8, the effects of δ_1 and δ_2 on the two objective functions can be seen more clearly and intuitively.

Table 6. Comparison of objective functions under different risk factors.

Risk Impact Factor		Transportation Cost		Transportation Risk		Algorithm Running Time
δ_1	δ_2	Value	Variation	Value	Variation	
0.3	0.7	129,174.11	6.60%	3942.58	−25.17%	82 s
0.4	0.6	122,941.08	1.46%	5071.63	−3.74%	82 s
0.5	0.5	121,172.85	—	5268.81	—	82 s
0.6	0.4	133,814.95	10.43%	6822.08	29.48%	76 s
0.7	0.3	132,813.10	9.61%	6602.57	25.31	83 s

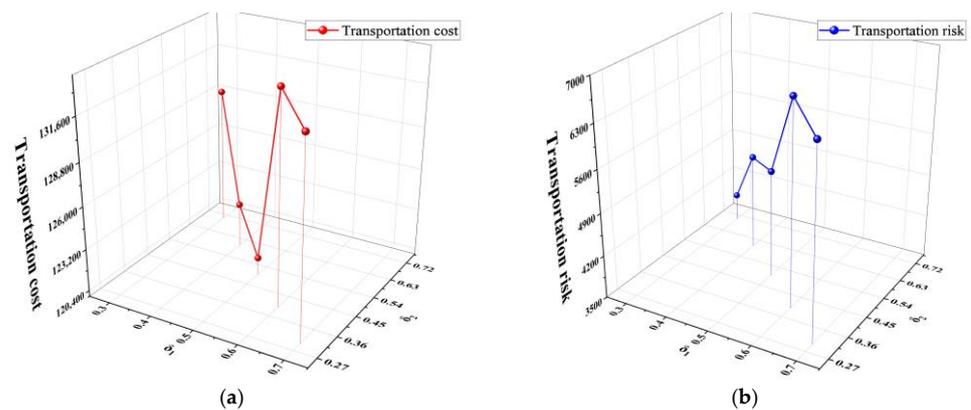


Figure 8. The impact of δ_1 and δ_2 on the objective functions. (a) Impact of δ_1 and δ_2 on transportation cost. (b) Impact of δ_1 and δ_2 on transportation risk.

From the analysis results, it can be observed that: (a) When the weight of risk impact factors changes, it affects the selection of distribution routes and the allocation of demand points, resulting in large fluctuations in transportation risks, and the transportation costs also change accordingly. (b) The impact of δ_1 and δ_2 on the objective function is not linear, so decision makers can adjust the factor weights to balance transportation costs and risks according to specific requirements.

5.3.3. Sensitivity Analysis of Credibility

As there are many uncertainties in emergency situations, it is difficult for decision makers to make immediate judgments about the importance of different constraints and limitations. In most cases, the need for medical supplies at the demand points should be met to the maximum extent possible in the shortest possible time, so the constraints on demand and traffic flow are equally important. This paper utilizes triangular fuzziness and fuzzy credibility theory to represent the uncertainty of demand and traffic flow and analyzes the sensitivity of each objective function to different credibility to reflect the impact of fuzzy credibility α_1 and α_2 on the objective function. Therefore, this study sets α_1 and α_2 to the same value, and starts with 0.5 as the adjustment of them. In order to show the relationship between the objective functions and credibility in a clearer and more detailed way, this research stipulates that $0.5 \leq \alpha_1 \leq 1.0$, $\alpha_1 = \alpha_2$, and the step of change is 0.05. The experimental results are illustrated in Figure 9.

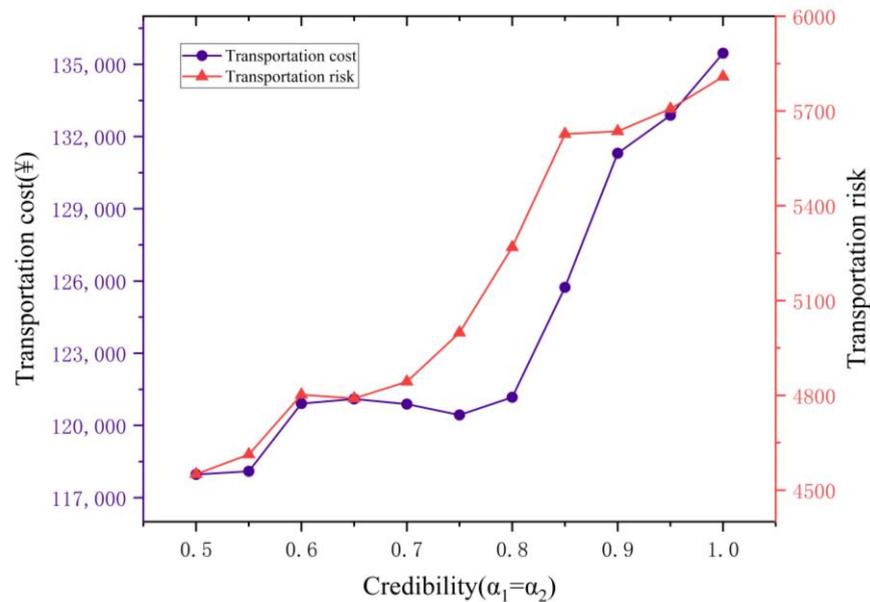


Figure 9. The sensitivity analysis of the objective function to credibility.

It can be observed that: (a) With the increase in credibility, the restrictions and requirements for distribution are more stringent, so the distribution process costs increase, and the transportation risk also rises. (b) The upward trend of the objective function is most pronounced when the credibility lies between [0.75, 0.90]. (c) When the credibility is greater than 0.9, the upward trend of the objective function becomes flat. Therefore, 0.9 is the turning point of reliability and its optimal value.

5.4. Effectiveness of MHNSGA-II and Performance Comparison

To verify the effectiveness of the improved MHNSGA-II, under the parameter settings in Section 5.2, this study compared the distribution route set and Pareto optimal solution obtained with NSGA-II [47].

5.4.1. Experimental Results of NSGA-II

The vehicle distribution route diagram calculated with NSGA-II and the comparison of the results of the two algorithms are represented in Figure 10 and Table 7. It can be seen that: (a) According to NSGA-II, all rescue centers need to be opened, and almost every rescue center needs to be equipped with three vehicles to provide services for the demand points, which increases the fixed cost in the transportation process. (b) The results of NSGA-II show that the vehicle distribution route of some rescue centers contains only one demand point, such as No. 3 and No. 4 rescue centers; this leads to higher vehicle fixed costs as well as higher transport distances and carbon emissions. (c) In the NSGA-II results, each rescue center has no fewer than two distribution vehicles, and the increase in the number of vehicles usage will lead to higher transport risks.

5.4.2. Comparison of Pareto Optimal Solution

This paper conducted 10 experiments, and took the best results for comparison. The comparison of the results of the Pareto optimal solution is shown in Figure 11. As can be seen from the figure: (a) MHNSGA-II yields a larger number of Pareto optimal solutions. (b) The optimal solution of MHNSGA-II is more uniformly distributed, and the Pareto curve is smoother. (c) The minimum value of the transportation cost of the original MHNSGA-II was 172,731.91, and the corresponding transportation risk value was 5570.78, which are 42.55% and 5.73% higher than the objective function value of the MHNSGA-II, respectively. The above conclusions confirm that MHNSGA-II has a more significant improvement on multi-objective problems and is superior to NSGA-II.

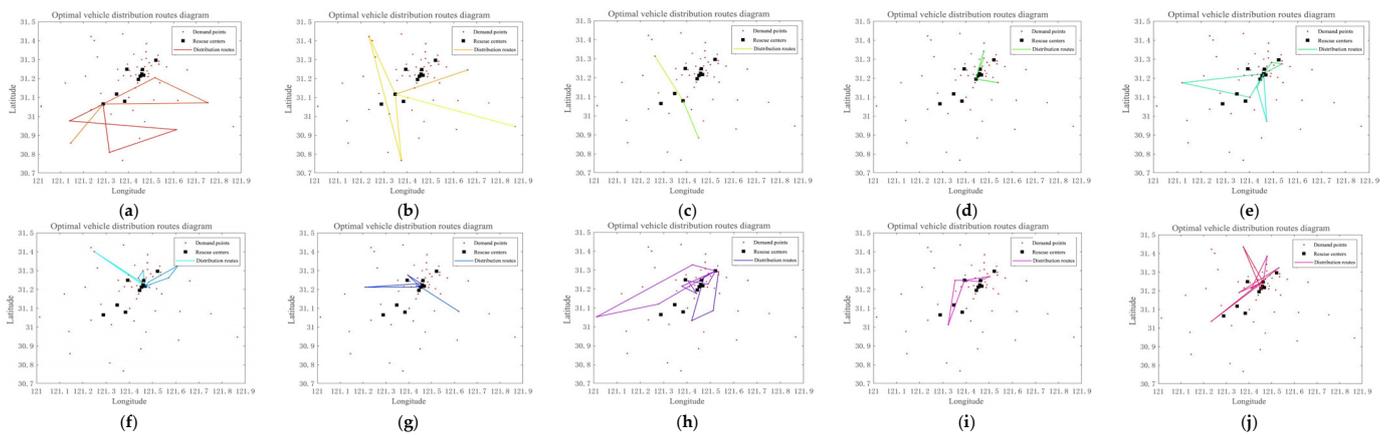


Figure 10. Vehicle distribution routes diagram based on NSGA-II. (a) Distribution routes of rescue center No. 1. (b) Distribution routes of rescue center No. 2. (c) Distribution routes of rescue center No. 3. (d) Distribution routes of rescue center No. 4. (e) Distribution routes of rescue center No. 5. (f) Distribution routes of rescue center No. 6. (g) Distribution routes of rescue center No. 7. (h) Distribution routes of rescue center No. 8. (i) Distribution routes of rescue center No. 9. (j) Distribution routes of rescue center No. 10.

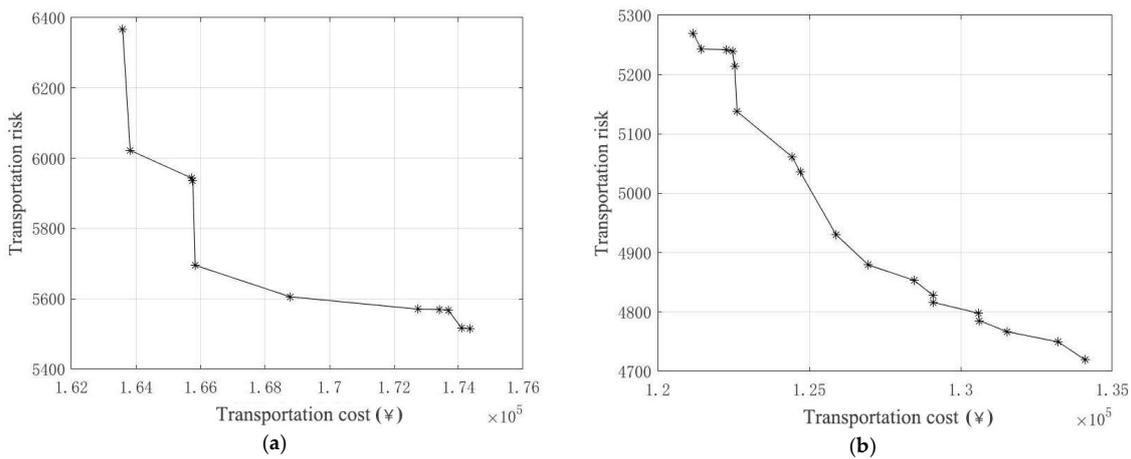


Figure 11. Pareto optimal solution comparison between NSGA-II and MHNSGA-II. (a) Pareto optimal solution of NSGA-II. (b) Pareto optimal solution of MHNSGA-II.

Table 7. Comparison of transport conditions under different risk factors.

Rescue Center No.	NSGA-II Result		MHNSGA-II Result	
	Number of Vehicles	Distribution Route	Number of Vehicles	Distribution Route
1	3	1-56-54-49-1	3	1-57-1
		1-60-63-1		1-58-56-54-1
		1-55-1		1-55-52-1
2	3	2-59-2	1	2-53-2
		2-41-57-2		
		2-61-2		

Table 7. Cont.

Rescue Center No.	NSGA-II Result		MHNSGA-II Result	
	Number of Vehicles	Distribution Route	Number of Vehicles	Distribution Route
3	2	3-42-3 3-53-3	3	3-59-61-3 3-41-63-62-3 3-60-64-3
4	3	4-27-4 4-64-4 4-40-4	3	4-65-4 4-30-27-26-4 4-29-28-32-4
5	3	5-32-28-5 5-34-46-5 5-20-52-5	3	5-24-25-5 5-12-23-17-22-36-35-5 5-47-5
6	3	6-13-43-6 6-14-26-6 6-11-58-62-6	3	6-19-16-31-34-6 6-18-39-38-15-6 6-20-13-42-6
7	3	7-65-7 7-24-17-45-7 7-23-7	3	7-14-37-21-7 7-11-43-7 7-40-7
8	3	8-15-35-36-31-8 8-21-19-25-12-8 8-38-47-48-8	—	—
9	2	9-16-29-9 9-50-44-9	3	9-51-44-46-9 9-49-50-48-9 9-33-45-9
10	3	10-22-39-10 10-33-30-51-10 10-18-37-10	—	—

6. Conclusions

This paper focuses on the problem of the distribution of emergency medical rescue supplies from rescue centers to demand points under sudden public events. On the premise of considering green and low-carbon distribution, the study establishes a multi-objective distribution optimization model for minimizing transportation cost and transportation risk under dual-uncertainty constraints. This research improved the original NSGA-II in various aspects, which were adopted to solve the proposed model. First, this paper used triangular fuzzy numbers to represent the uncertainties of the demand of supplies and the traffic flow in the distribution route and transformed the fuzzy constraints into an equivalent deterministic form through fuzzy credibility theory. Secondly, the study combined the vehicle, fuel, carbon emission, and time costs as the total transportation cost, and innovatively introduced the transportation risk of the dangerous goods distribution process into a proposed framework, developing the dual-objective distribution model that takes into account both transportation cost and transportation risk. Next, the proposed MHNSGA-II included two-stage encoding and multi-strategy hybrid improvement, which has significant advantages for solving multi-objective distribution optimization models. Finally, this research conducted a case study based on the real situation in Shanghai to verify the effectiveness of the improved algorithm and model. The results demonstrate that, compared with the original NSGA-II approach, MHNSGA-II can decrease the transportation cost and transportation risk by 42.55% and 5.73%, respectively. The sensitivity analysis assesses the validity and rationality of the proposed model, which can provide references for related decisions.

However, there are many limitations and challenges in the research. In the model construction and case study, more consideration is given to the influence of objective factors such as time and cost, while ignoring the subjective feelings of human psychology. Meanwhile, some data in the case study are difficult to access in real time, so they are replaced by random fuzzy numbers within a certain range, which deviate somewhat from the real situation. Based on these, it is necessary to further study relevant problems. In the process of distributing medical supplies, the number of supplies required

is different at each demand point, and there may be a situation of short supply. It is meaningful to further study the relationship between material scheduling and route optimization. In addition, from the perspective of the demanders, the urgency for medical supplies should be taken into account, and their psychological factors should be added to the process of route selection and optimization.

Author Contributions: Writing—original draft, Resources, S.P.; Writing—review and editing, Supervision, Q.L.; Visualization, J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by grants from National Natural Science Foundation of China (No. 71632008 and No. 71840003), Natural Science Foundation of Shanghai (No. 19ZR1435600), Humanity and Social Science Planning Foundation of the Ministry of Education of China (No. 20YJAZH068), and the science and technology development project of the University of Shanghai for Technology and Science (No. 2020KJFZ038).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors are indebted to the reviewers for their constructive comments, which greatly improved the contents and exposition of this paper.

Conflicts of Interest: The authors declare no conflict of interest.

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