Computers & Operations Research 146 (2022) 105912

Contents lists available at ScienceDirect

Computers and Operations Research

journal homepage: www.elsevier.com/locate/cor

Study on the optimization of urban emergency supplies distribution paths for epidemic outbreaks

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ARTICLE INFO

Keywords:
Epidemic outbreaks
Emergency supplies
Multi-verse optimizer algorithm
Urgency of demand
Heterogeneous vehicles

ABSTRACT

The humanitarian logistics vehicle routing problem (VRP) of urban emergency supplies in response to epidemic outbreaks is studied in this work to address the adverse effects of epidemic outbreaks on human society. Under the premise that the greater the urgency of the demand for various emergency supplies by the hospitals in the city's jurisdiction, the higher the priority of distribution, the fitness function of the highest vehicle utilization rate and the lowest transportation cost is established. The aim of the research is to construct a multi-objective mathematical model of emergency supplies distribution for large cities in case of an epidemic outbreak. Based on the multi-verse optimization algorithm and the differential evolution algorithm, a hybrid multi-verse optimizer algorithm based on differential evolution (DE-IMOV) is proposed. A simulation experiment is then carried out to verify the model. The calculation results show that the developed algorithm can effectively reduce the distribution cost and improve the full load rate of vehicles on the basis of considering the urgency of emergency supplies demand, which provides a solution for the optimization of heterogeneous vehicle distribution paths for urban emergency supplies in response to epidemic outbreaks.

1. Introduction

Epidemic outbreaks can result in serious damage to human society. Due to the destructiveness of such events and the limitation of emergency supplies, the distribution efficiency of the emergency supplies logistics distribution system is greatly reduced in an outbreak. This will result in various emergency supply problems, including the failure of timely delivery and the sharp increase in transportation costs (Farahani et al., 2020). Improving the efficiency of humanitarian logistics distribution of urban emergency supplies to meet the challenge of a pandemic outbreak has attracted extensive research attention. We take the city of Shijiazhuang in northern China as an example in this work, using data from the outbreak of coronavirus disease 2019 (COVID-19) from January to February 2021. During this time, hospitals (emergency supplies demand points) in various districts of the city required a large amount of various emergency supplies every day. The distribution of emergency supplies was further complicated by the varying urgency of demand for different emergency supplies at different hospitals, and the vehicle models for distributing emergency supplies were also different.

The logistics distribution of emergency supplies under the influence of an epidemic is a variant of the vehicle routing problem (VRP). Unlike other VRP variants that aim to minimize distribution costs (including environmental Macrina et al., 2019b and time costs Elshaer and Awad, 2020a), the distribution of emergency supplies under the influence of epidemics must also consider the rationality of emergency supplies distribution and the timeliness of transportation. That is, under multi-dimensional constraints, such as time windows and heterogeneous vehicles, supplies must be allocated reasonably, and the optimal distribution route of emergency supplies must be selected according to the demand urgency of different hospitals for different emergency supplies.

This study introduces the urgency of emergency supplies demand into the emergency supplies vehicle routing problem (ESVRP). According to the distribution characteristics of emergency supplies, on the premise of ensuring that the greater the demand urgency of each hospital for various emergency supplies, the higher the distribution priority, a multi-objective mathematical model is established that considers vehicle utilization and distribution costs. Further, using the differential evolution (DE) algorithm difference strategy as a reference, a verse difference operator is designed. On this basis, a random search enhancement mechanism based on a chaotic tent map is introduced,

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https://doi.org/10.1016/j.cor.2022.105912
Received 27 February 2021; Received in revised form 8 April 2022; Accepted 8 June 2022
Available online 21 June 2022

and a hybrid multi-verse optimizer algorithm based on the differential evolution (DE-IMOV) algorithm is developed. Finally, a simulation experiment is carried out based on data during the outbreak of COVID-19 from January to February 2021 in Shijiazhuang, a northern city of China. The simulation results show that the proposed algorithm has better uniformity and robustness than the biological heuristic algorithm and can effectively solve the problem of urban emergency supplies distribution path optimization in the event of an epidemic outbreak.

The remainder of this paper is organized as follows. Section 2 reviews the literature related to the humanitarian logistics and vehicle routing problem. Section 3 defines the problem and the corresponding mathematical description. The DE-IMOV algorithm is designed in Section 4, and the example is then analyzed and verified in Section 5. Finally, a summary and subsequent research directions are given in Section 6.

2. Literature review

The VRP problem has many variants and has been widely used in the fields of dangerous goods transportation (Mohri et al., 2020) and cold chain distribution (Theeb et al., 2020). However, most studies only aim at "minimum cost" when constructing the objective function. Richard P. Hornstra et al. established a cost model, including cost fitness functions such as route and goods picking costs (Hornstra et al., 2020). Ahmed Senoussi et al. studied the vehicle routing problem of a single manufacturer providing products to multiple retailers (Senoussi et al., 2018) and designed a heuristic algorithm based on a genetic algorithm to solve the problem. However, this study was only aimed at minimizing the distribution cost. Literature (Yu et al., 2019; Macrina et al., 2019a) studied the green vehicle routing problem from the perspective of sustainable development, taking the minimum carbon emission cost as the optimization goal. On this basis, Zizhen et al. studied the vehicle routing problem involving the distribution of outsourcing companies and considered the profit balance of such companies as well as the distribution costs (Zhang et al., 2020). However, it should be pointed out that the above fitness functions are not applicable to the vehicle routing problem of emergency supplies distribution due to the scarcity of transport capacity resources during the outbreak of epidemics.

As an important link of disaster risk reduction (DRR), humanitarian logistics is a research hotspot worldwide (Ghorbani and Ramezanian, 2020; Moura et al., 2020). Literature (Yoon and Albert, 2020; Enayati et al., 2018) studied an ambulance scheduling problem following a disaster, aiming to save the injured and reduce losses to the greatest extent. Based on the background of urban flooding, a multi-type emergency vehicle fleet scheduling model was established in Xu et al. (2018) to solve the problem of vehicle supply shortages caused by the sharp increase in rescue demand after natural disasters. In terms of emergency supplies distribution, Seyed Reza et al. studied the emergency supplies scheduling problem considering inventory levels and established a mathematical model to minimize distribution costs (Abazari et al., 2021). Aakil M. Caunhye et al. studied single emergency supplies scheduling problems (Caunhye et al., 2016), while the fairness of the distribution of humanitarian emergency supplies was explored in Sakiani et al. (2020) and Huang and Rafiei (2019). On this basis, Zhong et al. (2020) studied the distribution of emergency supplies that did not meet the quantities required at demand points, which had a certain reference significance for urban emergency supplies distribution in response to an epidemic outbreak.

In addition, in order to ensure the priority of emergency material distribution, the urgency of each hospital's demand for various types of emergency materials should be considered. Ref. Tang et al. (2019) incorporates the urgency of customer orders into the supply chain scheduling problem, which has certain reference significance for the establishment of the emergency material demand urgency model. Ref. Guan et al. (2020) is based on the entropy weight method to measure the urgency of the disaster area (demand point). However, it should be pointed out that without the guidance of relevant experts, the weights calculated according to the entropy weight method have a high risk of distortion. Cheraghi, S. et al. established a blood distribution model based on the urgency of the wounded. When calculating the urgency of the wounded, similar to the Analytic Hierarchy Process (AHP), the urgency of the wounded was determined according to the different injuries of the wounded. On this basis, the literature (Jianyou et al., 2020; Hu et al., 2019) established a corresponding evaluation index system based on the AHP to evaluate the urgency of the demand for emergency supplies, but the above two studies have problems such as insufficient corresponding indicators of the indicator layer.

As the vehicle routing problem is a complex and coupled multi-objective optimization problem, the solution result of the accurate algorithm in solving this kind of problem is not ideal. Taking the urban emergency supplies distribution route optimization problem in response to epidemic outbreaks as an example, vehicle utilization, the demand urgency of emergency supplies demand points, and the distribution cost must be comprehensively considered when designing an algorithm to solve the model. These three objectives are coupled; that is, under the condition of ensuring vehicle utilization and distribution priority, a re-planning of the distribution route may be required. Therefore, the algorithms related to vehicle routing optimization are mostly heuristic algorithms (Lucas et al., 2019; Elshaer and Awad, 2020b). Particle swarm optimization (PSO) (Anisul Islam et al., 2021), genetic algorithm (GA) (Ghannadpour and Zandiyeh, 2020), differential evolution (DE) algorithm (Sethanan and Jamrus, 2020), and their improved versions are mostly used in the existing research. Scholars have attempted to apply the metaheuristic algorithm multi-verse optimizer (MVO) to optimization fields such as unmanned aerial vehicle (UAV) track planning (Kumar et al., 2018) and achieved some success. Therefore, it is feasible to apply the improved MVO algorithm to optimize urban emergency supplies distribution paths in response to an epidemic outbreak.

The above research indicates that the urgent demand for various emergency supplies by hospitals should be considered due to the limitation of emergency supplies during the outbreak of epidemics and the transportation capacity constraints of distribution companies. Therefore, models with the single goal of minimizing the distribution costs are no longer applicable. In addition, in the relevant research on the distribution of humanitarian emergency supplies, most studies only explore a single category of emergency supplies and a single model of vehicle distribution, which is not realistic in an actual epidemic outbreak. Therefore, based on the background of epidemic outbreaks, this paper studies the distribution of emergency supplies. The main contributions are summarized as follows:

(1) Under the premise of ensuring that the more urgent the demand of various hospitals for various types of emergency materials, the higher the priority of delivery, and with the goal of improving the utilization rate of transport resources and reducing the cost of delivery, a multi-objective mathematical model of emergency materials delivery is established.

(2) This paper studies the distribution of heterogeneous vehicles with different types of emergency materials, which is more in line with the actual situation of emergency material distribution in the event of epidemic outbreak, so as to deal with the adverse impact of epidemic outbreak on human society.

(3) The verse difference operator and random search enhancement mechanism based on a chaotic tent map are designed, which are introduced into the multi-verse optimizer algorithm, and a hybrid multi-verse optimizer algorithm based on differential evolution is developed.

(4) Experiments show that the developed algorithm is better than the other four algorithms including biological heuristic algorithm.

Table 1
Evaluation index system of demand urgency of emergency supplies demand points.

Target layer A	Criterion layer B	Index layer C
Demand urgency of emergency supplies demand points	Infection situation B1	Population in the jurisdiction C11 Number of new inflow C12 Confirmed cases C13 Newly confirmed cases C14
	Medical infrastructure situation B2	Number of hospital beds C21 Number of medical staff C22
	Emergency supplies reserve situation B3	Gap degree of certain emergency supplies C31

3. Model establishment

3.1. Problem description

Following an epidemic outbreak, hospitals in various districts of a city require a lot of emergency supplies, including oxygen, disposable protective clothing, and food. Due to the characteristics of frequent logistics activities and a large amount of information, short transportation distance, high timeliness requirements, many types of transportation, and small batches, the solution to the general VRP is no longer applicable. How to efficiently distribute urban emergency supplies in an epidemic outbreak and realize the fair distribution and timely delivery of such supplies has become an urgent problem for humanitarian logistics.

When an epidemic occurs, each city will set up emergency supplies distribution centers to efficiently distribute emergency supplies. Emergency supplies distribution centers store different types of emergency supplies. According to the different needs of each hospital, different types of emergency supplies are delivered to each hospital by different types of vehicles. Before building a model, make reasonable assumptions as follows: (1) In the process of distribution, each emergency supply required by each hospital is generally distributed by only one vehicle. That is, when the weight and volume of a certain emergency supply needed by a hospital are both smaller than the maximum loading volume of the distribution vehicle, it cannot be split and distributed by multiple vehicles; (2) Different kinds of emergency supplies required by the same hospital can be loaded on different vehicles; (3) Due to the particularity of emergency supplies distribution, the vehicle control regulations formulated by the city in terms of transportation are ignored; (4) Emergency supplies are generally distributed by a corresponding carrier company, so the vehicle does not need to return to the emergency supplies distribution center after the distribution task is completed.

3.2. Data selection

We use the data from https://cn.bing.com/maps of the Shijiazhuang road network in this work. An undirected graph $G = (V, E)$ is then established for hospitals and emergency supply distribution centers in Shijiazhuang. Set $V = \{0, 1, \dots, V_{\max}\}$ is a set of points representing the nodes composed of hospitals and emergency supplies distribution centers in each jurisdiction, where the emergency supplies distribution center is 0. Set $E = \{e_{12}, e_{23}, \dots, e_{pr}\}, (\forall p, r \in V)$ is a set of arcs representing the distance between nodes.

3.3. Demand urgency model of emergency supplies demand point

Due to the limitations of emergency supplies and the transportation capacity and resources of distribution companies, the urgency of the demand for various emergency supplies by each hospital should be considered when distributing emergency supplies in an epidemic outbreak. In order to further improve the corresponding indicators in the index layer of the demand urgency evaluation index system, based on the "wounded urgency evaluation index system" established in Cheraghi and Hosseini-Motlagh (2020), this paper further includes the new inflow and outflow population and newly confirmed cases and hospital beds in the jurisdiction into the evaluation system. An evaluation index system of the demand urgency of emergency supplies demand points (hospitals) is established, as shown in Table 1, and the evaluation system is improved to make it more scientific and reasonable. This paper studies the distribution of heterogeneous emergency supplies. Compared with the research in literature (Cheraghi and Hosseini-Motlagh, 2020), this work has more practical significance for the optimization of urban emergency supplies distribution paths in response to the outbreak of an epidemic.

Table 2
Symbol description of demand urgency model of emergency supplies demand point.

Symbol description	
ϑ	Original data of each index of each hospital index layer
I	Type set of emergency supplies, $I = \{1, 2, \dots, i\}$
J	Set of hospital, $J = \{1, 2, \dots, j\} = V \setminus \{0\}$
ξ_{ji}	Demand urgency value of hospital j for emergency materials i
γ_{ji}	The numerical value of the relative demand urgency of hospital j for emergency supplies i
$\xi_{\min}$	Minimum urgency of hospital j's demand for emergency supplies i

The symbols used in the model are given in Table 2.

Since the measurement units of each index in the index layer are not unified, the data of each index must be normalized (standardized), as shown below.

$$C^* = \frac{(\vartheta - \vartheta_{\min})}{(\vartheta_{\max} - \vartheta_{\min})} \tag{1}$$

where C^* is the standardized value of each index of each hospital index layer, and $\vartheta_{\max}, \vartheta_{\min}$ are the maximum and minimum values of the original data of each index of each hospital index layer, respectively.

The urgency of the demand for various materials in each hospital is then obtained as:

$$\xi_{ji} = \sum_{r=1}^{k} \omega_r \times C_{jir} \tag{2}$$

Among them, ω_r is the weight of each indicator r of the indicator layer on the urgency of demand, $r \in \{1, 2, \dots, k\}$, and k is the total number of indicators. C_{jir} is the standardized value of hospital j's evaluation index r for material i. Experts score the weight of each indicator in the indicator layer, collect and process the data, list the judgment matrix, and further use SPSS software to process the data.

Finally, calculate the value γ_{ji} of the relative demand urgency of hospital j for material i, and take the hospital with the smallest demand urgency as the benchmark, there are:

$$\gamma_{ji} = \frac{\xi_{ji}}{\xi_{\min}} \tag{3}$$

3.4. Optimization model of urban emergency supplies distribution path

The limited capacity resources of emergency material carriers and the satisfaction of each hospital when the epidemic breaks out must be considered. In order to make effective use of transport capacity resources and reduce resource waste, vehicle utilization, i.e., load

Table 3
Symbol description of the optimization model of the urban emergency supply distribution path.

Symbol description	
N	Set of types of vehicles for distributing emergency supplies, $N = \{1, 2, \dots, n\}$
A	Set of vehicles for distributing emergency supplies, $A = \{1, 2, \dots, a\}$
a, n	Vehicle a is of type n
$W_j^{a,n}$	Weight of emergency supplies sent by vehicle a to hospital j
$V_j^{a,n}$	Volume of emergency supplies sent by vehicle a to hospital j
W_{ji}	Weight of type i emergency supplies required by hospital j
V_{ji}	Volume of type i emergency supplies required by hospital j
$\eta_{a,n}$	Stowage utilization of vehicle a
τ	The sum of stowage utilization of all distribution vehicles
Q	Freight per unit time for transporting emergency materials
F_a	Transportation cost of vehicle a
L_{0j}	The distance from the emergency material distribution center to each hospital, $L_{0j} = e_{0j}, \forall j \in J$
L_{jk}	The distance from hospital$j$to hospital k, $L_{jk} = e_{jk}, \forall j \in J; \forall k \in J$
$\overline{V}$	Average speed of each vehicle, $\overline{V} = 50$ km/h
$T_{a,ji}^{actual}$	Time when vehicle a actually delivers emergency material i to hospital j
$T_{a,ji}$	Hospital j requires vehicle a to deliver emergency supplies i at the latest delivery time
T_{La}	Loading time of vehicle a
$N_{n\max}$	Maximum number of vehicles with model n
H_{SUM}	Total number of hospitals required to distribute emergency supplies

utilization and volume utilization, is introduced into the model. The distribution route optimization model of urban emergency materials established in this paper also includes the distribution cost in order to increase profits for the carrier company. Some symbols used in the model are given in Table 3.

3.4.1. Vehicle utilization

Vehicle utilization rate mainly considers the two aspects of load and volume utilization rates. Generally, the mixed loading of multiple batches of goods is optimized based on the experience of warehouse managers. In this paper, the larger of the two is taken as the evaluation standard, as follows:

$$\eta_{an} = \{\frac{\sum_{j\in J} W_j^{a,n}}{W_{\max,n}}, \frac{\sum_{j\in J} V_j^{a,n}}{V_{\max,n}}\}, \forall a \in A; \forall n \in N \tag{4}$$

where $W_{\max,n}$ is the maximum loading weight of the vehicle with model n and $V_{\max,n}$ is the maximum loading volume of the vehicle with model n. The calculation methods of $W_j^{a,n}$ and $W_j^{a,n}$ are shown in Eqs. (5) and (6).

$$W_j^{a,n} = \sum_{i\in I} W_{ji} \times \psi_{ji}^{a,n}, \forall j \in J; \forall a \in A; \forall n \in N \tag{5}$$

$$V_j^{a,n} = \sum_{i\in I} V_{ji} \times \psi_{ji}^{a,n}, \forall j \in J; \forall a \in A; \forall n \in N \tag{6}$$

$$\psi_{ji}^{a,n} \in \{0, 1\}, \forall j \in J; \forall a \in A; \forall n \in N; \forall i \in I \tag{7}$$

Eq. (7) is a 0–1 variable, which indicates whether vehicle a with model n distributes type$i$emergency supplies required by hospital j.

$$\tau = \sum_{a\in A} \eta_{a,n}, \forall n \in N \tag{8}$$

3.4.2. Vehicle transportation cost

The calculation formula of transportation cost of vehicle is shown in Eq. (9).

$$F_a = Q \times \frac{L_{0j}}{\overline{V}} \times \sigma_{0j}^a + \sum_{j,k\in J} (Q \times \frac{L_{jk}}{\overline{V}} \times \sigma_{jk}^a), \forall a \in A; \forall j \in J \tag{9}$$

$$\sigma_{0j}^a \in \{0, 1\}, \forall a \in A; \forall j \in J \tag{10}$$

$$\sigma_{jk}^a \in \{0, 1\}, \forall a \in A; \forall j, k \in J \tag{11}$$

Eq. (10) is a 0–1 variable, which indicates whether vehicle a will directly transport the emergency materials required by hospital j from emergency material distribution center 0 to the hospital j. Eq. (11) is a 0–1 variable, which indicates whether vehicle$a$will directly transport the emergency supplies required by hospital k from hospital j to hospital k.

3.4.3. Objective function and constraints

The formula of the mathematical model established in this paper is as follows:

$$\max f = \frac{1}{\sum_{a\in A} F_a} \times \tau \times \sum_{j\in J} \sum_{i\in I} \left(\gamma_{ji} \times \varepsilon_{ji}\right) \tag{12}$$

$$\varepsilon_{ji} \in \{0, 1\}, \forall j \in J; \forall i \in I \tag{13}$$

$$T_{a,ji}^{actual} = T_{La} + \frac{L_{0k}}{\overline{V}} \times \sigma_{0k}^a + \sum_{k,j\in J} (\frac{L_{kj}}{\overline{V}} \times \sigma_{kj}^a), \forall a \in A; \forall k \in J \tag{14}$$

$$\sum_{j\in J} W_j^{a,n} \le W_{\max,n}, \forall a \in A; \forall n \in N \tag{15}$$

$$\sum_{j\in J} V_j^{a,n} \le V_{\max,n}, \forall a \in A; \forall n \in N \tag{16}$$

$$\sum_{j\in J} \lambda_j^{a,n} \le 5, \forall a \in A; \forall n \in N \tag{17}$$

$$\sum_{a\in A} \beta_{an} \le N_{n\max}, \forall n \in N \tag{18}$$

$$\sum_{j\in J} \psi_{ji}^{a,n} = H_{SUM}, \forall i \in I; \forall a \in A; \forall n \in N \tag{19}$$

$$\lambda_j^{a,n} \in \{0, 1\}, \forall j \in J; \forall a \in A; \forall n \in N \tag{20}$$

$$\beta_{an} \in \{0, 1\}, \forall a \in A; \forall n \in N \tag{21}$$

Eq. (12) is the objective function, which includes minimizing the transportation cost of distribution vehicles and maximizing the loading utilization rate of distribution vehicles and the demand urgency value of emergency materials delivered before the latest time required by the hospital. Among them, in the third part of the objective function, $\sum_{j\in J} \sum_{i\in I} \left(\gamma_{ji} \times \varepsilon_j\right)$ is to maximize the demand urgency value of emergency materials delivered before the latest delivery time required by the hospital, indicating that the higher the demand urgency, the higher the priority of distribution.

Eq. (13) is a 0–1 variable, which indicates whether the emergency materials$i$ are delivered before the latest delivery time required by hospital j, when $T_{a,ji}^{actual} \le T_{a,ji}$, $\varepsilon_{ji} = 1$; when $T_{a,ji}^{actual} > T_{a,ji}$, $\varepsilon_{ji} = 0$. The calculation method of the time $T_{a,ji}^{actual}$ when vehicle actually delivers emergency materials i to hospital j is shown in Eq. (14).

Eqs. (15) and (16) are the maximum loading weight limit and maximum loading volume limit of the vehicle, respectively; Eq. (17) indicates that a standard van can traverse up to five hospitals in one distribution operation; Eq. (18) is the maximum number limit of vehicles of each model; Eq. (19) indicates that various materials

Table 4
Expert scoring results.

Index	C11	C12	C13	C14	C21	C22	C31
C11	1	2	1	1	4	3	1
C12	0.5	1	0.5	0.5	2	2	0.5
C13	1	2	1	1	4	3	1
C14	1	2	1	1	5	4	1
C21	0.25	0.5	0.25	0.2	1	0.2	0.2
C22	0.33	0.5	0.33	0.25	5	1	0.25
C31	1	2	1	1	5	4	1

Table 5
Expert scoring results.

m-order	3	4	5	6	7	8	9
RI value	0.52	0.89	1.12	1.26	1.36	1.41	1.46

required by each hospital must be delivered to each hospital without omission; Eq. (20) is a 0–1 variable, which indicates whether vehicle a with model n arrives at hospital j; Eq. (21) is a 0–1 variable indicating whether vehicle a with model n performs the distribution task.

3.5. Weight calculation of each index of index layer on demand urgency

The analytic hierarchy process (AHP) analytic hierarchy process is used to calculate the weight of expert scoring. Firstly, six relevant experts are consulted by back-to-back communication, and the weight of each index is scored. To reduce the subjective influence factors of experts, the maximum and minimum scores of the collected data are removed to calculate the average value. The judgment matrix (paired comparison matrix) is shown in Table 4.Considering that expert scoring is prone to the influence of expert subjective factors, it is necessary to test the consistency of judgment matrix to ensure that the error is within the acceptable range so as to ensure that the urgency of demand is consistent with the actual situation of epidemic relief.

In this paper, λ is used to represent the eigenvalue of matrix B, then the maximum eigenvalue of matrix B is $\lambda_{\max}$. The calculation method of consistency index CI is shown in Eq. (22). The closer the CI value is to 0, the better the consistency of matrix B. Further, in order to evaluate the CI value, the random consistency index RI is introduced. The value of RI is related to the order of the judgment matrix, as shown in Table 5. On this basis, the consistency ratio CR is calculated according to the CI value and RI value. The specific calculation method is shown in Eq. (23). Among them, the better the CR value, the better the consistency of judgment matrix B. When CR < 0.1, it indicates that judgment matrix B meets the consistency test and its inconsistency is within the allowable range.

$$CI = \frac{\lambda_{\max} - m}{m - 1} \tag{22}$$

where m is the order of the judgment matrix.

$$CR = \frac{CI}{RI} \tag{23}$$

Online SPSS analysis software is then used to calculate the expert scoring weight, and the calculation results are shown in Table 6. The consistency test results are shown in Table 7.

It can be seen from Table 7 that the consistency ratio CR value is $0.030 < 0.1$, indicating that the judgment matrix satisfies the consistency test, and the calculated weights are consistent.

4. Hybrid multi-verse optimizer algorithm based on differential evolution

4.1. Basic multi-verse optimizer algorithm

The multi-verse optimizer (MVO) is a natural heuristic algorithm proposed by Seyedali Mirjalili et al. (2016). Compared with other traditional intelligent optimization algorithms, such as the PSO algorithm, MVO has the advantages of fewer parameters and better convergence accuracy at a faster optimization speed and shows excellent searchability.

Table 6
AHP analytic hierarchy process results.

Index	Feature vector	Weight value
C11	1.326	18.939%
C12	0.692	9.885%
C13	1.326	18.939%
C14	1.422	20.319%
C21	0.279	3.989%
C22	0.533	7.609%
C31	1.422	20.319%

Table 7
Expert scoring results.

Maximum characteristic root $\lambda_{\max}$	CI value	RI value	CR value
7.426	0.041	1.360	0.030

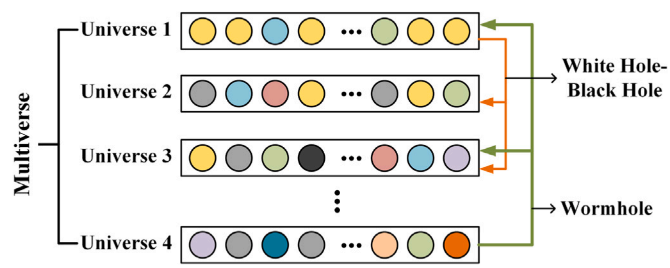

Fig. 1. Schematic diagram of matter exchange in the multi-verse.

The algorithm simulates the process by which each universe in the multi-verse exchanges matter with other universes through white holes, black holes, and wormholes. Each dimension of the problem represents a piece of matter in the universe, the matter possessed by the universe represents a candidate solution to the problem, and the random universe is represented as follows:

$$P = \begin{bmatrix} X_1 = \left\{x_1^1, x_1^2, \ldots, x_1^m\right\} \\ X_2 = \left\{x_2^1, x_2^2, \ldots, x_2^m\right\} \\ \vdots \\ X_n = \left\{x_n^1, x_n^2, \ldots, x_n^m\right\} \end{bmatrix} \tag{24}$$

where n is the number of the universe, m is the amount of matter in the universe, and x_n^m is the mth matter of the nth universe.

Meanwhile, the fitness of the candidate solution represents the expansion degree of the universe. In the iterative process, each candidate solution is a black hole; the probability of a universe with good fitness becoming a white hole is higher, and the probability of a universe with poor fitness becoming a black hole is higher. The universe receives the material sent from the optimal universe through wormholes or exchanges material with other universes through white holes and black holes. Other universes can transmit objects to the current optimal universe through wormholes under a certain probability, regardless of the expansion rate. The schematic diagram of matter exchange in the multi-verse is shown in Fig. 1.

The basic MVO algorithm flow is as follows:

Step 1. Initialize the parameters to generate the initial universe;

Step 2. Calculate and standardize the expansion degree of the universe;

Step 3. Update the wormhole existence probability (WEP) and the traveling distance rate (TDR);

Step 4. Exchange verse material using the following process:

a. For each universe, generate a random number r_1 between 0 and 1. If r_1 is less than the standard expansion rate of the universe, the roulette

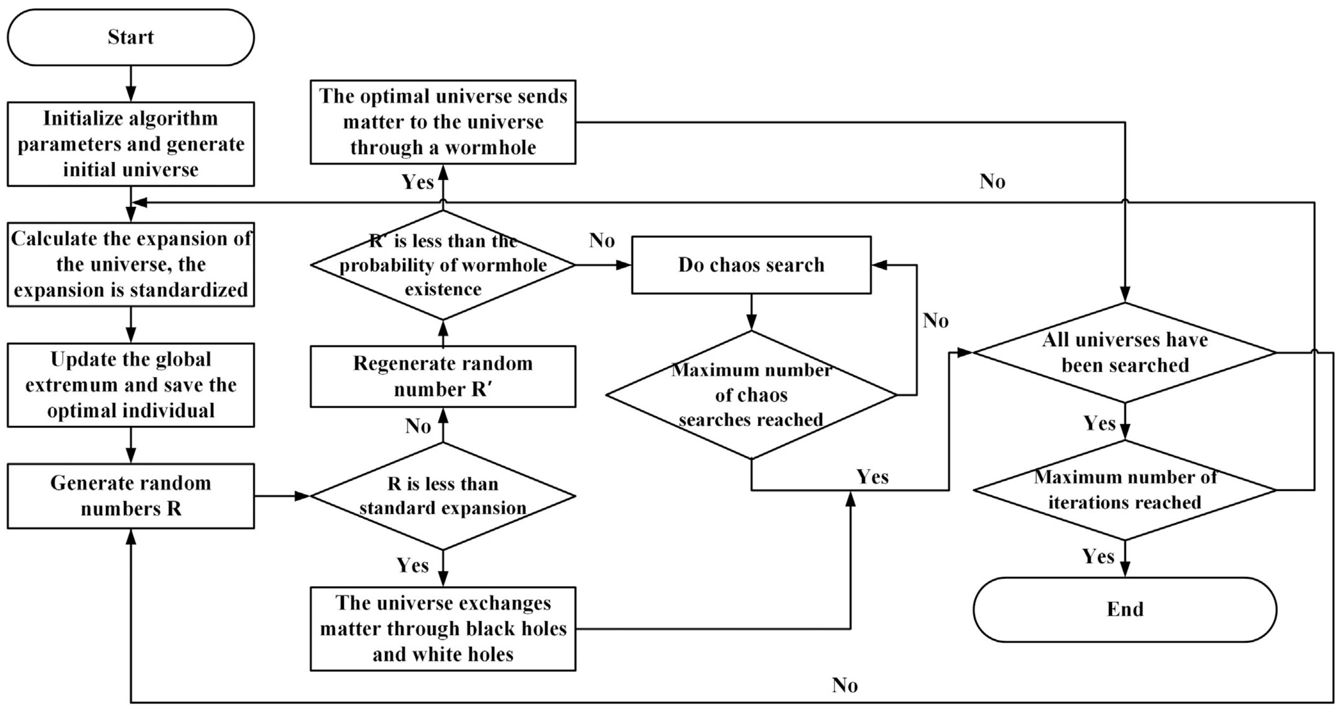

Fig. 2. Flowchart of hybrid multi-verse optimizer algorithm based on differential evolution.

wheel is used to select the universe that produces the white hole, the universe with the black hole sends matter to the universe that produces the white hole, and the dimensions of the black hole and the white hole are replaced.

b. If r_1 is greater than the standard expansion rate, a random number r_2 between 0 and 1 is generated for the universe. If r_2 is less than the wormhole existence probability, the universe receives the material sent from the optimal universe through the wormhole.

c. If r_2 is greater than the probability of wormhole existence, the universe will not operate.

Step 5. If the maximum number of iterations is reached, exit the optimization and output the result; if not, return to Step 2.

4.2. Improvement of MVO algorithm

The model problem in this paper is complex, with large dimensions and many constraints, which makes the objective function very sensitive to individual changes. The MVO algorithm using global update strategy often has unsatisfactory results for this kind of model. Chaotic tent map mapping has the characteristics of randomness, ergodicity and sensitivity to initial conditions. Introducing it into the basic MVO algorithm can greatly enhance the global search ability and the ability to jump out of local extremum of MVO algorithm. The differential mutation operator in differential evolution algorithm can well regulate the diversity of population and improve the search ability of the algorithm. Therefore, when solving the mathematical model in this paper, the verse difference operator and the random search enhancement mechanism based on a chaotic tent map are introduced on the basis of the multi-verse optimization algorithm, which makes the algorithm more suitable for solving the model in this paper. The algorithm flow chart is shown in Fig. 2.

4.3. Solution scheme

The requirements of different hospitals for materials are continuous; that is, the hospital's demand for a certain material can be delivered by multiple vehicles, but using this solution will complicate the problem

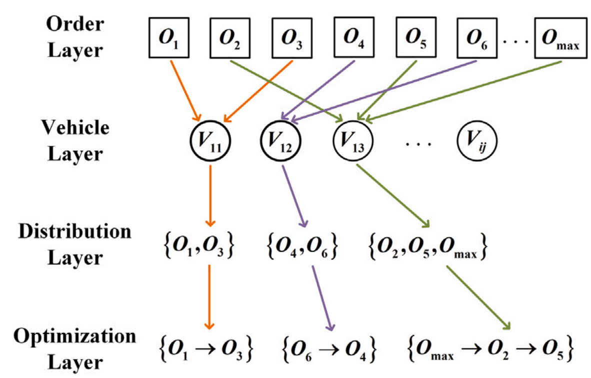

Fig. 3. Schematic diagram of problem-solving scheme.

and reduce the optimization effect of the algorithm. Therefore, the model is discretized, meaning that a hospital's demand for a certain material can only be transported by one vehicle, and the vehicle is used as a variable for optimization. The number of hospitals is multiplied by the type of materials, i.e., the number of orders. For a batch of orders, a random integer between 1 and the total number of vehicles is generated for each order, representing the order for the number of vehicles to transport. A visualization of this process is shown in Fig. 3.

4.4. Improved hybrid MVO algorithm

Before describing the algorithm, we first give some symbolic descriptions of the improved hybrid MVO algorithm in Table 8.

Step 1: Parameter initialization

Parameters include the universe dimension D, the number of universes NP, the number of iterations G, the crossover probability CR, the difference coefficient F, the upper limit of the search space $x_{\max}$, the lower limit of the search space $x_{\min}$, the vehicle speed $\overline{V}$, and the unit time freight Q.

Step 2: Multi-verse initialization

Table 8
Symbolic description of the improved hybrid MVO algorithm.

Symbol description	
X_i^k	The ith universe in the kth iteration
X_{best}^k	The optimal universe in the kth iteration
$X_i^k(d)$	The dth matter of the ith universe in the kth iteration
O_i	ith order
N_o	Total number of orders
a, n	Vehicle a is of type n
$N_{n\max}$	Total number of vehicles
$fit\left(X_i^k\right)$	The expansion degree of the ith universe in the kth iteration
$Sfit\left(X_i^k\right)$	The standard expansion degree of the ith universe in the kth iteration
S	Maximum chaotic search times
l_S	Search step size of cosmic chaos search strategy

Initialize the loop according to the total number of orders N_0, and generate random integers between 1 and N_v for each order. After the loop is completed, calculate the order owned by each vehicle and determine all routes for the delivery order. Calculate the delivery path with the least time, and judge whether the path meets the constraints. If it meets the constraints, add it to the multi-verse. If it does not, repeat this step until the multi-verse has NP universes that meet the constraints.

Step 3: Calculate and standardize the expansion degree of the universe

Calculate the expansion degree of each universe according to the objective function value (fitness function value). In this model, the universe with the largest expansion represents the optimal solution, so the universe that does not meet the constraints is assigned negative infinity. Use the normalization formula to normalize the expansion of the universe:

$$Sfit(X_i^k) = \frac{fit(X_i^k) - \min(fit([X_1^k, X_2^k, \dots, X_{NP}^k]))}{\max(fit([X_1^k, X_2^k, \dots, X_{NP}^k])) - \min(fit([X_1^k, X_2^k, \dots, X_{NP}^k]))} \tag{25}$$

Step 4: Update the global extreme value and save the universe with the largest expansion as X_{best}^k

Step 5: The universe exchanges matter through black holes and white holes

A random number r_i^1 between 0 and 1 is generated for each universe X_i^k. If $r_i^1 < Sfit\left(X_i^k\right)$, the universe X_j^k that generates the white hole is selected according to the roulette method. The universe with the black hole sends matter to the universe that created the white hole, and the black hole and white hole dimensions change. The process is denoted in Eq. (26).

$$X_i^k(d) = \begin{cases} X_j^k(d), r_i^1 < Sfit(X_i^k) \\ X_i^k(d), r_i^1 \geq Sfit(X_i^k) \end{cases} \tag{26}$$

Step 6: Verse differential

If $r_i^1 > Sfit\left(X_i^k\right)$, a random number r_i^2 between 0 and 1 is generated for the universe. If $r_i^2 < WEP$, then a random number r_i^3 is generated, and the optimal universe sends matter to the universe through the wormhole, as shown in Eq. (27).

$$X_i^k = \begin{cases} \left\lfloor X_{best}^k + F \times (X_j^k - X_k^k) \right\rfloor, r_i^2 < WEP \& r_i^3 < 0.5 \\ \left\lfloor X_{best}^k - F \times (X_j^k - X_k^k) \right\rfloor, r_i^2 < WEP \& r_i^3 \geq 0.5 \\ X_i^k, r_i^2 > WEP \end{cases} \tag{27}$$

Step 7: Random search based on a chaotic tent map

If $r_i^2 > WEP$, perform a chaos search on the universe as follows:

Table 9
Distance matrix (unit: km).

\	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12
G1	0	6.4	4.6	7.8	50	32	20	30	11	47	14	7.4
G2	6.4	0	5.2	10	44	37	19	28	14	46	19	6.5
G3	4.6	5.2	0	11	47	39	17	36	17	44	16	4.5
G4	7.8	10	11	0	49	32	27	18	8.1	55	23	13.9
G5	50	44	47	49	0	86	32	66	57	38	61	49
G6	32	37	39	32	86	0	55	35	23	82	41	36
G7	20	19	17	27	32	55	0	44	36	30	31	17.7
G8	30	28	36	18	66	35	44	0	22	73	37	34
G9	11	14	17	8.1	57	23	36	22	0	55	20	20.8
G10	47	46	44	55	38	82	30	73	55	0	52	38
G11	14	19	16	23	61	41	31	37	20	52	0	13.2
G12	7.4	6.5	4.5	13.9	49	36	17.7	34	20.8	38	13.2	0

a. Generate the random number r_i^4 in the interval $\left[\left(x_{\max} - x_{\min}\right), 2\left(x_{\max} - x_{\min}\right)\right]$ and calculate the minimum search step l_0, as shown in Eq. (28).

$$l_0 = \frac{x_{\max} - x_{\min}}{r_i^4} \tag{28}$$

b. Generate a random number r_i^5 in the interval $[-0.5, 0.5]$, where the search strategy for universe chaos is shown in Eq. (29).

$$X_i^{k'} = \left\lfloor X_i^k + 0.5 r_i^5 \times l_s \times (x_{\max} - x_{\min}) + x_{\min} \right\rfloor \tag{29}$$

c. Update the search step size, as shown in Eq. (30).

$$l_{s+1} = \begin{cases} 2l_s, x_{\min} < l_s < \frac{x_{\max} - x_{\min}}{2} \\ 2l_s - 1, \frac{x_{\max} - x_{\min}}{2} \leq l_s < x_{\max} \end{cases} \tag{30}$$

d. Calculate the expansion degree of the universe and perform individual updates, as shown in Eq. (31).

$$X_i^k = \begin{cases} X_i^{k'}, fit(X_i^{k'}) > fit(X_i^k) \\ X_i^k, fit(X_i^{k'}) \leq fit(X_i^k) \end{cases} \tag{31}$$

Step 8: If the maximum number of iterations is reached, exit the optimization and output the result, otherwise return to Step 3.

5. Simulation experiment and analysis

5.1. Simulation experimental data

5.1.1. Model data

Shijiazhuang is a city in northern China with a population of 10 million. The data used in the simulation is taken between January and February 2021, during the epidemic prevention and control period in Shijiazhuang, to ensure that the city's emergency supplies can be in place when necessary. The source code is from https://cn.bing.com/maps, and http://tjj.sjz.gov.cn/col/1585199536734/2020/02/26/1582685809908.html data is used for the modeling and simulation experiment.

The city is divided into 11 jurisdictions, each of which has a hospital (the emergency material demand point), and the address of the distribution center is Zhonghua N Ave, Xinhua District, Shijiazhuang, Hebei, China. The distance matrix between the distribution center and each hospital is shown in Table 9. The total number of hospitals that need to distribute emergency supplies is $H_{SUM} = 11$, and a description of the symbols in Table 9 is shown in Table 10. The models and specifications of the delivery vehicles owned by the carrier are shown in Table 11. The average vehicle speed of each model is 50 km/h, and the freight per unit time for emergency material transportation is 58.5$/h. The parameters of emergency resources are shown in Table 12, the index parameters of each index layer are shown in Table 13, and the gap rate and demand of emergency materials in each hospital are shown in Table 14.

The symbols I-11-1, I-11-2 and I-11-3 in Table 11 are described as follows.

Table 10
Symbols and their representations in Table 9.

Symbols and their representations	
G1	Changan District (The Fourth Hospital of Hebei Medical University and Hebei Cancer Hospital)
G2	Qiaoxi District (The Third hospital of Hebei Medical University)
G3	Xinhua District (The Second Hospital of Hebei Medical University)
G4	Yuhua District (The First hospital of Hebei Medical University)
G5	Jingxing Mining Area (Jingxing Mining District Hospital)
G6	Gaocheng District (Gaocheng People's Hospital)
G7	Luquan District (Luquan People's Hospital)
G8	Luancheng District (Luancheng People's Hospital)
G9	High-Tech Zone (The Fourth Hospital of Shijiazhuang)
G10	Pingshan County (Pingshan Zhongshan Hospital)
G11	Zhengding County (Zhengding County People's Hospital)
G12	Distribution center (Zhonghua N Ave, Xinhua District, Shijiazhuang, Hebei.)

Table 11
Models and specifications of vehicles carried by carriers.

Vehicle model	Symbol	I-11–1	I-11–2	I-11-3
Standard van-4.2 m	$n = 1$	6	15	5
Standard van-5.2 m	$n = 2$	10	17	5
Standard van-6.8 m	$n = 3$	13	30	5

Table 12
Emergency supplies parameters.

Emergency supplies	Symbol	Ratio of weight to volume
Oxygen (40 liter can)	$i = 1$	1.7 m^3/Ton
Disposable protective clothing	$i = 2$	12.66 m^3/Ton
Food	$i = 3$	3 m^3/Ton

a. I-11-1: Maximum loading weight of vehicle (Unit: Ton)
b. I-11-2: Maximum loading volume of vehicle (Unit: m^3)
c. I-11-3: Maximum number of vehicles

5.1.2. Experimental environment and algorithm parameters

The MVO algorithm, the biological heuristic algorithm PSO algorithm, the whale optimization algorithm (WOA), and the differential evolution (DE) algorithm are selected to compare with the DE-IMVO algorithm proposed in this paper. The algorithm programming tool adopts MATLAB (R2016a), the operating system is Windows 10, the computer memory is 16 GB, the CPU is Intel i7-8750H, and the parameters of the DE-IMVO algorithm are set as follows: The universe dimension $D = 33$, the number of universes $NP = 20$, the number of iterations $G = 500$, the crossover probability $CR = 0.2$, the difference coefficient $F = 0.5$, the upper limit of the search space$x_{\max} = 15$, the lower limit of the search space $x_{\min} = 1$, the vehicle speed $v = 50$, and the unit time freight $M = 58.5$. Among them, each hospital requires emergency supplies to arrive at 8:30 a.m. every day, $T_{a,ji} = 8 : 30$. The loading time of each vehicle is 6:30 a.m. every day, and the loading time of each delivery vehicle is one hour.

The symbols I-14-1, I-14-2,I-14-3 and I-14-4 in Table 14 are described as follows.

a. I-14-1: Hospital
b. I-14-2: Types of emergency supplies
c. I-14-3: Gap degree
d. I-14-4: Demand quantity (Unit: Ton)

5.2. Simulation results and analysis

Fifty operations were performed for each of the five algorithms. The calculation results are described as follows. Among them, the urgency of demand for emergency supplies required by hospitals in each jurisdiction is shown in Table 15.

5.2.1. Randomly select a single simulation experiment

In the calculation process, each of the five algorithms DE, PSO, WOA, MVO, and DE-IMVO were run fifty times. The fitness function convergence curve of a random selection is shown in Fig. 4. Table 16 shows the comparison results of the freight, the number of hospitals that failed to deliver the emergency materials before the required delivery time of each hospital, and the total number of vehicles used in the emergency materials distribution vehicle route planning scheme solved by the random selection of the five algorithms during a certain operation. Index 2 refers to the number of hospitals that fail to deliver emergency materials before the time required by each hospital.

In this running process, the distribution path, the distance, and the freight of each distribution vehicle solved by the DE-IMVO algorithm are shown in Table 17. As shown in Fig. 4, the DE-IMVO algorithm designed in this paper has the highest convergence accuracy and greatly improves the solution performance of the MVO algorithm compared with the original MVO algorithm. At the same time, compared with the other three biological heuristic algorithms, the DE-IMVO algorithm has excellent performance in solving the emergency material distribution problem. Table 16 shows that when the number of vehicles used is the same, only the DE-IMVO algorithm can complete the distribution task of all hospitals before the required delivery time of emergency materials, which ensures that hospitals with greater demand urgency for all kinds of emergency materials have a higher distribution priority. Further, in this distribution process, compared with the other four algorithms, the distribution cost of the DE-IMVO algorithm is reduced between 5.14% and 17.62%, which greatly reduces the distribution cost of emergency materials.

5.2.2. Results and analysis of 50 simulation experiments

In the calculation process, the five algorithms DE, PSO, WOA, MVO, and DE-IMVO were run 50 times. Table 18 shows the comparison table (average value) of each index in the emergency material distribution scheme solved in the process of running the five algorithms 50 times, where Index 4 is the number of hospitals that do not receive the emergency materials after the deadline for delivery required by each hospital. The results of 20 operations of five algorithms are randomly selected and shown in Table 19. In the calculation process of the five algorithms over 50 iterations, the average fitness function convergence curve is shown in Fig. 5.

It can be seen from the above simulation experimental data that the average objective function value obtained by the developed DE-IMVO algorithm is 16.46%, 33.17%, and 8.16% higher than those of the DE, PSO, and WOA algorithms in the 50 runs, respectively. Tables 18 and 19 show that when the MVO algorithm solves the optimization problem of heterogeneous vehicle distribution paths for urban emergency supplies in response to epidemic outbreaks, and the phenomenon that the optimization result is often negative infinity often occurs. This is due to its poor ability to seek optimization in the process of such large-scale optimization problems and its lack of ability to jump out of local extreme values. The optimization result is often

Table 13
Indicator parameters of each indicator layer.

Jurisdiction	Index					
	C11 (1×10^4 People)	C12 (People)	C13 (case)	C14 (case)	C21	C22 (People)
Changan District	83.55	1824	11	2	2420	4457
Qiaoxi District	85.44	1912	6	1	2218	3546
Xinhua District	71.51	1547	3	0	2816	5432
Yuhua District	57.61	1209	15	2	2000	2631
Jingxing Mining Area	10.07	467	0	0	490	455
Gaocheng District	79.01	1631	547	74	440	420
Luquan District	47.81	848	2	0	200	331
Luancheng District	36.23	537	3	2	490	544
High-Tech Zone	37.52	591	8	2	280	290
Pingshan County	50.28	1175	1	0	190	185
Zhengding County	51.7	1204	18	1	420	700

Table 14
Gap rate and demand for emergency supplies in each hospital.

I-14-1	I-14-2	I-14-3	I-14-4	I-14-1	I-14-2	I-14-3	I-14-4
	$i = 1$	45%	3		$i = 1$	40%	2.4
G1	$i = 2$	20%	0.8	G7	$i = 2$	20%	0.8
	$i = 3$	15%	1		$i = 3$	5%	0.5
	$i = 1$	20%	1.5		$i = 1$	30%	1.3
G2	$i = 2$	40%	1	G8	$i = 2$	50%	1
	$i = 3$	36%	2		$i = 3$	20%	0.8
	$i = 1$	18%	1		$i = 1$	20%	1
G3	$i = 2$	35%	0.8	G9	$i = 2$	45%	1.2
	$i = 3$	15%	1.3		$i = 3$	15%	1
	$i = 1$	25%	2		$i = 1$	15%	0.6
G4	$i = 2$	50%	1	G10	$i = 2$	55%	1.2
	$i = 3$	20%	1.5		$i = 3$	10%	0.6
	$i = 1$	15%	0.8		$i = 1$	20%	1
G5	$i = 2$	25%	0.5	G11	$i = 2$	40%	1.5
	$i = 3$	10%	1		$i = 3$	18%	1
	$i = 1$	80%	5				
G6	$i = 2$	75%	1.8				
	$i = 3$	30%	1.5				

Table 15
Demand urgency values for emergency supplies needed by hospitals in each jurisdiction.

Hospital	Emergency supplies		
	$i = 1$	$i = 2$	$i = 3$
G1	0.5522	0.4291	0.5249
G2	0.4482	0.5062	0.6896
G3	0.4086	0.4509	0.4768
G4	0.3147	0.3954	0.3882
G5	0.0000	0.0000	0.0000
G6	1.0000	1.0000	1.0000
G7	0.2284	0.1169	0.1066
G8	0.1478	0.2059	0.1856
G9	0.1130	0.1858	0.1456
G10	0.1668	0.3042	0.1823
G11	0.2149	0.2677	0.2824

Table 16
Comparison table of five algorithms for solving vehicle scheduling indicators for emergency material distribution.

Index	Algorithm				
	DE	PSO	WOA	MVO	DE-IMVO
Freight	544.94	522.67	487.12	538.64	463.32
Index 2	3	4	1	4	0
Number of vehicles used	15	15	15	15	15

Table 17
DE-IMVO algorithm calculation results.

Vehicle number	Route	Number of hospitals delivered	Route length	Freight ($)
V-(1,1)	G1(i2) → G4 (i3)	2	16.1	18.837
V-(1,2)	G3 (i2) (i3)	1	4.5	5.265
V-(1,3)	G7 (i2)	1	17.7	20.709
V-(1,4)	G7 (i3) → G5 (i1) (i2) (i3)	2	49.7	58.149
V-(1,5)	G7 (i1) → G10 (i1) (i3)	2	47.7	55.809
V-(2,1)	G11 (i3)	1	13.2	15.444
V-(2,2)	G2 (i1) → G9 (i1) → G6 (i1)	3	43.5	50.895
V-(2,3)	G4 (i1) (i2)	1	13.9	16.263
V-(2,4)	G10 (i2)	1	38	44.46
V-(2,5)	G11 (i1) → G9 (i3)	2	33.2	38.844
V-(3,1)	G2 (i2) → G8 (i1) (i2) (i3)	2	34.5	40.365
V-(3,2)	G6 (i2) (i3)	1	36	42.12
V-(3,3)	G2 (i3)	1	6.5	7.605
V-(3,4)	G3 (i1) → G1 (i1) → G9 (i2)	3	20.1	23.517
V-(3,5)	G1 (i3) → G11 (i2)	2	21.4	25.038

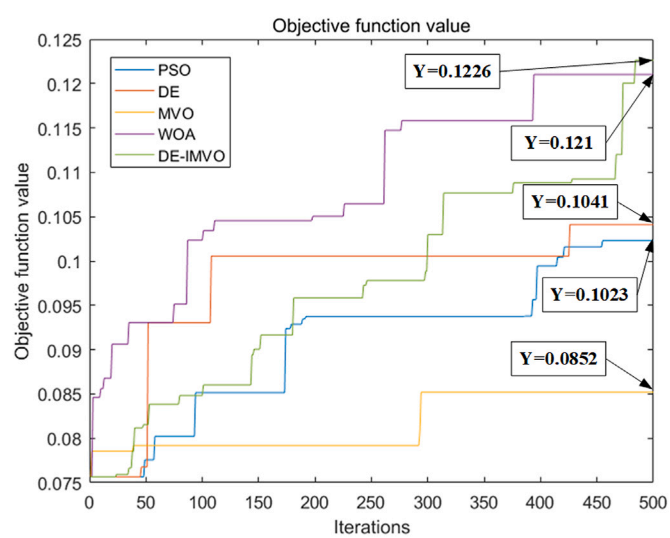

Fig. 4. Convergence curve comparison of the fitness function of a random selection of a running process.

assigned as -inf because it does not meet the constraints. It can be seen from Fig. 5 that the DE-IMVO algorithm designed in this paper has the characteristics of high convergence accuracy, good uniformity, and robustness, which greatly improves the optimization performance of the MVO algorithm. In terms of reducing distribution costs, the developed DE-IMVO algorithm is 14.95%, 11.21%, 30.43%, and 8.33% lower than DE, PSO, MVO, and WOA, respectively. Table 19 shows that during 50 runs, only the DE-IMVO algorithm can complete delivery to all hospitals before the required delivery time of emergency materials, ensuring the priority of emergency materials delivery.

5.2.3. The worst running result of each algorithm during 50 runs.

Fig. 6 shows the worst running results of each algorithm during 50 runs. As illustrated, in the case of the worst running results of each

Table 18
Comparison of the average results of the five algorithms run 50 times.

Index	Algorithm				
	DE	PSO	WOA	MVO	DE-IMVO
Total length of the journey (km)	465.8	446.5	569	431.7	396
Average vehicle time (h)	0.621	0.595	0.759	0.576	0.528
Total shipping ($)	544.93	522.113	666.023	505.44	463.32
Index 4	2	2	5	1	0
Average objective function value	0.09051	0.08335	-inf	0.1017	0.11

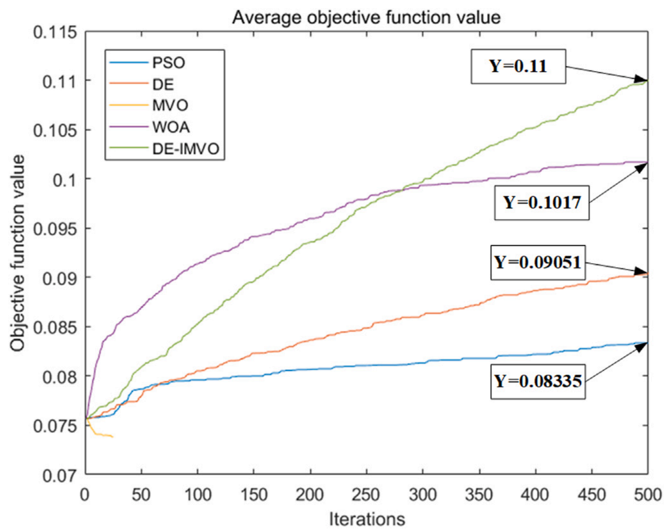

Fig. 5. Convergence curve of average fitness function in the calculation process of the five algorithms run 50 times.

Table 19
Data table of fitness values of randomly selected 20 simulation experiments.

DE	PSO	WOA	MVO	DE-IMVO
0.089	0.076	0.101	0.076	0.107
0.088	0.089	0.097	0.070	0.106
0.099	0.088	0.095	0.076	0.108
0.086	0.081	0.102	0.076	0.111
0.089	0.076	0.102	0.070	0.114
0.091	0.086	0.094	0.076	0.112
0.096	0.081	0.109	0.072	0.110
0.087	0.094	0.101	-inf	0.105
0.092	0.087	0.085	0.067	0.102
0.085	0.087	0.096	0.084	0.114
0.097	0.082	0.101	0.076	0.107
0.090	0.082	0.118	0.076	0.104
0.100	0.102	0.101	-inf	0.104
0.092	0.081	0.085	0.076	0.123
0.084	0.081	0.099	0.076	0.106
0.095	0.092	0.110	0.070	0.109
0.092	0.083	0.104	0.076	0.111
0.087	0.080	0.102	-inf	0.110
0.092	0.078	0.093	0.076	0.113
0.091	0.078	0.087	0.075	0.119

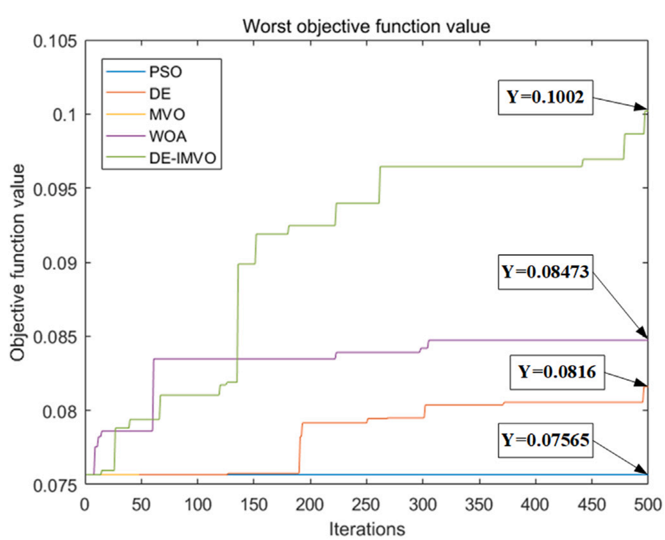

Fig. 6. Worst convergence curves of the five algorithms.

algorithm, DE-IMVO still has a high convergence accuracy, and the fitness function value is 15.44%, 18.56%, and 24.5% higher than that of the WOA, DE, and PSO algorithms, respectively, which further verifies its performance. Therefore, it can be concluded that the developed DE-IMVO algorithm greatly improves the performance of the MVO algorithm. Thus, the proposed optimization scheme can effectively solve the humanitarian logistics problem in an epidemic outbreak.

6. Conclusion

The distribution of urban emergency supplies in response to an epidemic outbreak was studied in this work, as a variant of the VRP, using the northern Chinese city of Shijiazhuang as a case study. A heterogeneous emergency material demand urgency evaluation system was constructed, which employed the population in the jurisdiction, the new inflow and outflow population, new confirmed cases, confirmed cases, hospital beds, and the number of medical staff as the evaluation indicators. Further, the urgency of hospital demand, the minimization of distribution costs, the time window, maximization of vehicle full load rate, and some practical constraints were also considered to build a mathematical model of emergency material distribution. A DE-MVO algorithm was then developed to optimize the distribution path of urban emergency supplies in response to epidemic outbreaks. Finally, a simulation experiment was generated based on the historical data of Shijiazhuang and compared with four other algorithms. The results showed that the total cost of the DE-IMVO algorithm was reduced between 8.33% and 30.43%, compared with the other algorithms. Because AHP is easily affected by subjective factors of experts and has certain limitations, we will focus on the distribution of emergency materials based on fuzzy AHP in future research.

This study on urban humanitarian logistics in response to the outbreak of the epidemic makes the following contributions: (a) The established mathematical model takes into account the demands of hospitals and emergency supplies carriers when the disease breaks out; (b) The developed DE-IMVO algorithm significantly improves the performance of the MVO algorithm and reduces the distribution cost by 30.43%; (c) According to the example verification, our research can be effectively applied to the distribution of urban emergency supplies in response to epidemic outbreaks.

CRediT authorship contribution statement

Haishi Liu: Conceptualization, Methodology, Writing – original draft, Software. **Yuxuan Sun:** Software, Validation, Writing – original draft. **Nan Pan:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Yi Li:** Data curation, Validation. **Yuqiang An:** Writing – review & editing, Investigation. **Dilin Pan:** Methodology, Investigation.

Acknowledgments

This work was supported in part by the Science and Technology Project of Yunnan China Tobacco Industry Co., Ltd (grant number: 2018QT05); and in part by the Technology project of Hongyun Honghe Tobacco (Group) Co., Ltd (grant number: HYHH2021XX004; HYHH2020XX003). All authors have read and agreed to the published version of the manuscript.

References

Abazari, Seyed Reza, Aghsami, Amir, Rabbani, Masoud, 2021. Prepositioning and distributing relief items in humanitarian logistics with uncertain parameters. Socio-Econ. Plan. Sci. 74, 100933.

Anisul Islam, Md., Gajpal, Yuvraj, ElMekkawy, Tarek Y., 2021. Hybrid particle swarm optimization algorithm for solving the clustered vehicle routing problem. Appl. Soft Comput. 110, 107655.

Caunhye, Aakil M., Zhang, Yidong, Li, Mingzhe, Nie, Xiaofeng, 2016. A location-routing model for prepositioning and distributing emergency supplies. Transp. Res. E: Logist. Transp. Rev. 90, 161–176.

Cheraghi, Sara, Hosseini-Motlagh, Seyyed-Mahdi, 2020. Responsive and reliable injured-oriented blood supply chain for disaster relief: a real case study. Ann. Oper. Res. 291, 129–167.

Elshaer, Raafat, Awad, Hadeer, 2020a. A taxonomic review of metaheuristic algorithms for solving the vehicle routing problem and its variants. Comput. Ind. Eng. 140, 106242.

Elshaer, Raafat, Awad, Hadeer, 2020b. A taxonomic review of metaheuristic algorithms for solving the vehicle routing problem and its variants. Comput. Ind. Eng. 140, 106242.

Enayati, Shakiba, Mayorga, Maria E., Rajagopalan, Hari K., Saydam, Cem, 2018. Real-time ambulance redeployment approach to improve service coverage with fair and restricted workload for EMS providers. Omega 79, 67–80.

Farahani, Reza Zanjirani, Lotfi, M.M., Baghaian, Atefe, Ruiz, Rubén, Rezapour, Shabnam, 2020. Mass casualty management in disaster scene: A systematic review of OR & MS research in humanitarian operations. European J. Oper. Res. 287 (3), 787–819.

Ghannadpour, Seyed Farid, Zandiyeh, Fatemeh, 2020. An adapted multi-objective genetic algorithm for solving the cash in transit vehicle routing problem with vulnerability estimation for risk quantification. Eng. Appl. Artif. Intell. 96, 103964.

Ghorbani, Milad, Ramezanian, Reza, 2020. Integration of carrier selection and supplier selection problem in humanitarian logistics. Comput. Ind. Eng. 144, 106473.

Guan, Gaofeng, Lin, Zijun, Gong, Yu, Jiang, Zhijuan, 2020. Modeling and simulation of collaborative dispatching of disaster relief materials based on urgency. Math. Probl. Eng. 2020, 4274106.

Hornstra, Richard P., Silva, Allyson, Roodbergen, Kees Jan, Coelho, Leandro C., 2020. The vehicle routing problem with simultaneous pickup and delivery and handling costs. Comput. Oper. Res. 115, 104858.

Hu, H., Chen, K., He, J., Zhang, Y., Zhou, J., Han, Y., 2019. Scenario-based emergency material scheduling using V2X communications. Electronics 8 (6), 707.

Huang, Kai, Rafiei, Rezvan, 2019. Equitable last mile distribution in emergency response. Comput. Ind. Eng. 127, 887–900.

Jianyou, Zhao, Wanli, Han, Wenjie, Zheng, Yang, Zhao, 2020. Distribution of emergency medical supplies in cities under major public health emergency. J. Traffic Transp. Eng. 20 (3), 168–177.

Kumar, P., Garg, S., Singh, A., Batra, S., Kumar, N., You, I., 2018. MVO-based 2-D path planning scheme for providing quality of service in UAV environment. IEEE Internet Things J. 5 (3), 1698–1707.

Lucas, Flavien, Billot, Romain, Sevaux, Marc, 2019. A comment on What makes a VRP solution good? The generation of problem-specific knowledge for heuristics. Comput. Oper. Res. 110, 130–134.

Macrina, Giusy, Laporte, Gilbert, Guerriero, Francesca, Pugliese, Luigi Di Puglia, 2019a. An energy-efficient green-vehicle routing problem with mixed vehicle fleet, partial battery recharging and time windows. European J. Oper. Res. 276 (3), 971–982.

Macrina, Giusy, Pugliese, Luigi Di Puglia, Guerriero, Francesca, Laporte, Gilbert, 2019b. The green mixed fleet vehicle routing problem with partial battery recharging and time windows. Comput. Oper. Res. 101, 183–199.

Mohri, Seyed Sina, Asgari, Nasrin, Farahani, Reza Zanjirani, Bourlakis, Michael, Laker, Benjamin, 2020. Fairness in hazmat routing-scheduling: A bi-objective stackelberg game. Transp. Res. E: Logist. Transp. Rev. 140, 102006.

Moura, Eduardo Henrique de, Cruz, Tibério Bruno Rocha e., Chiroli, Daiane Maria De Genaro, 2020. A framework proposal to integrate humanitarian logistics practices, disaster management and disaster mutual assistance: A Brazilian case. Saf. Sci. 132, 104965.

Sakiani, Reza, Seifi, Abbas, Khorshiddoust, Reza Ramazani, 2020. Inventory routing and dynamic redistribution of relief goods in post-disaster operations. Comput. Ind. Eng. 140, 106219.

Senoussi, Ahmed, Dauzère-Pérès, Stéphane, Brahimi, Nadjib, Penz, Bernard, Mouss, Nadia Kinza, 2018. Heuristics based on genetic algorithms for the capacitated multi vehicle production distribution problem. Comput. Oper. Res. 96, 108–119.

Sethanan, Kanchana, Jamrus, Thitipong, 2020. Hybrid differential evolution algorithm and genetic operator for multi-trip vehicle routing problem with backhauls and heterogeneous fleet in the beverage logistics industry. Comput. Ind. Eng. 146, 106571.

Tang, Liang, Jin, Zhihong, Qin, Xuwei, Jing, Ke, 2019. Supply chain scheduling in a collaborative manufacturing mode: model construction and algorithm design. Ann. Oper. Res. 275, 685–714.

Theeb, Nader Al, Smadi, Hazem J., Al-Hawari, Tarek H., Aljarrah, Manar H., 2020. Optimization of vehicle routing with inventory allocation problems in Cold Supply Chain Logistics. Comput. Ind. Eng. 142, 106341.

Xu, G., Wang, J., Huang, G.Q., Chen, C.-H., 2018. Data-driven resilient fleet management for cloud asset-enabled urban flood control. IEEE Trans. Intell. Transp. Syst. 19 (6), 1827–1838.

Yoon, Soovin, Albert, Laura A., 2020. A dynamic ambulance routing model with multiple response. Transp. Res. E: Logist. Transp. Rev. 133, 101807.

Yu, Yang, Wang, Sihan, Wang, Junwei, Huang, Min, 2019. A branch-and-price algorithm for the heterogeneous fleet green vehicle routing problem with time windows. Transp. Res. B 122, 511–527.

Zhang, Z., Qin, H., Li, Y., 2020. Multi-objective optimization for the vehicle routing problem with outsourcing and profit balancing. IEEE Trans. Intell. Transp. Syst. 21 (5), 1987–2001.

Zhong, Shaopeng, Cheng, Rong, Jiang, Yu, Wang, Zhong, Larsen, Allan, Nielsen, Otto Anker, 2020. Risk-averse optimization of disaster relief facility location and vehicle routing under stochastic demand. Transp. Res. E: Logist. Transp. Rev. 141, 102015.