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Optimal allocation of material dispatch in emergency events using multi-objective constraint for vehicular networks

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Abstract
In the early stage of large-scale disasters, the first batch of emergency supplies are often in short supply, and decision-makers responsible for material distributions need to send emergency materials to the recipients in the shortest possible time, while also taking into account the minimum transportation costs. In these scenarios, the traditional particle swarm algorithm has been frequently used, however it faces the challenge of "precocious puberty" and is unable to resolve the scheduling problem. To solve this issue, this paper proposes an optimization model for material dispatch in emergency events using a non-dominant sorting algorithm for vehicular communication. The model first satisfies the shortest delivery time and material demand, establishes the shortest route for vehicle travel, and then proposes a multi-objective uncontrolled solving ant colony algorithm to break through the bottleneck of the juvenile algorithm by solving the problems of convergence of NSGA-II algorithm and uneven distribution of Pareto front surface. Moreover, the objective function and constraints for vehicles at each emergency supply point are defined, which must not exceed the total number of available vehicles. The case study shows that the Pareto non-inferior solution searched by NSGA-II is ideal under the premise that multiple goals are optimal, and the Pareto non-inferior solution scheme available for researchers to choose is improved. The model and algorithm objectively optimize the overall layout of emergency material distribution.

Keyword Multi-objective constraints; vehicular networks; emergency events; optimal distribution of materials

1 Background

A plethora of new road safety applications and use cases have emerged for safer and more efficient travel due to the convergence of wireless communication and vehicular networks. The basis of road safety applications is the accurate collection of traffic data and the subsequent transmission of that data in real time. Vehicles utilize the status information of other vehicles, including speed, direction, and position etc. to acquire application-specific objectives [1]. The application-specific objectives and scenarios have motivated the research community to excel the research in various domains of vehicular communication. The emergence of unmanned aerial vehicles (UAVs) and fog-enabled vehicles has provided an opportunity to explore new research domains on an unprecedented scale. Emergency tasks, e.g. people search and rescue missions assigned to UAVs are typically time-sensitive, as they are a life-or-death situation in the aftermath of a tragedy. The interplay of UAVs with fog-enabled vehicles has the ability to run highly demanding tasks with strict latency requirements, taking into account limited computing resources and harsh energy supply replenishment for UAVs in post-disaster relief operations [2].

Disaster management, on the other hand, is always a challenging task for rescue operators. In the US alone, every year 60,000 people die due to disasters at the expense of 150 billion USD of damages [2]. It is a serious sudden disruption, triggered by man-made or natural hazards. In such scenarios, immediate response and proper management can play a vital role in disaster management, thus the

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loss can be reduced [3]. Disaster management involves strategically organizing resources and the supply chain, which are often an uphill battle, thus there is a need for technological support in order to cope with a disaster. The utilization of vehicular networks could be the best solution for the supply chain in disaster management as they are increasingly affordable, reliable, and portable. Thus the integration of Vehicular Networks for rescue missions can reduce the mortality rate and increase the chances of survivors [4].

In this paper, we proposed an optimization model for supply chain for disaster management. In the first stage, the model calculates the minimum delivery time to figure out a shortest path for optimal allocation of material dispatch in emergency events. Our main contribution in the study are as follows:

- We propose an optimization model for material dispatch in emergency situations utilizing a non-dominant sorting algorithm for vehicular communication.
- The proposed model establishes the shortest route for vehicle travel by satisfying the shortest delivery time and material need.
- To overcome the juvenile algorithm's bottleneck, we propose a multi-objective uncontrolled solving ant colony algorithm that addresses the NSGA-II algorithm's convergence issues as well as the unequal distribution of the Pareto front surface.

The rest of the paper is organized as follows; recent work related to the proposed approach is presented in Sect. 2. Section 3 presents the material distribution and model construction, design of the algorithm is proposed in Sect. 4 and finally Sect. 6 concludes the paper after the testing and analysis phase in Sect. 5.

2 Related work

In [5], a technology based on the non-dominant sorting genetic algorithm-II (NSGA-II) is proposed to solve the problem of distribution optimization of emergency supplies, which is simpler and more efficient than the traditional genetic algorithm-based method, does not require weighting factors, and can solve the optimization problem of multi-objective and multi-constraint. In this work, taking into account factors such as emergency material capacity, demand at disaster points, and total number of delivery vehicles, based on the simulation results of four different material distributions, it is found that the number of iterations based on the NSGA-II algorithm increases, and the increase in the abundance of the Pareto solution will increase the uniformity of the distribution. The authors in [6] solve an example of a multi-objective constraint with two objective functions and six constraints, using an exact algorithm and an approximation algorithm, which is an appropriately modified version of the multi-criteria branching and delimitation algorithm. In addition, through the analysis of experimental results, the work concludes that SPEA and NSGA-II can solve the same problem, but the precise algorithm surface, they are in the calculation of the optimal boundary, the NSGA-II algorithm boundary is smoother and clearer.

The ability of the best-first search in the vs/or search space in multi-objective constraint optimization is proposed and evaluated in [7]. The main advantage of the AND/OR representation of the search space is the speed. In the benchmarks of stochastic and true multi-objective constrained optimization, the superiority of the optimal optimization method over depth priority and branch boundary search is proved. Emergency supplies vehicle distribution is a very important and realistic issue that affects the recovery time of an area after a disaster and the avoidance of secondary disasters. To solve the problem of emergency material distribution, the most important thing is the two goals of speed and cost. On the surface of the example, the algorithm in [8] can combine the crowded density sorting mechanism and the non-dominant solution sorting mechanism with the cross-variation operation operator of the genetic algorithm to obtain a better Pareto solution set, which is an algorithm that meets the Open Location-Routing Problem (OLRP) solution requirements. For emergency relief from uncertain disasters and needs, build an emergency dispatch model from multiple targets to the place where the material is sent. In [9], initially the uncertainty of emergency material demand is studied, and then the multi-objective function and constraint function are constructed. The multi-objective optimization model is established, and finally the target combination optimization model is modified by algorithmic test. The results show that the method has strong adaptability and good performance in emergency rescue, which verifies the rationality of the model and the feasibility of the algorithm.

In view of the problem that emergency rescue needs to achieve the shortest completion time and the largest average full load rate of transportation, the authors propose a material distribution model through the analysis of the diversity, limitation, maximum load and maximum capacity of transportation in [10]. The model is based on a multi-objective constraint algorithm that constructs integral iterations, non-negative solution space constraints, and hyper plane constraints to update the speed of particles. Numerically, the optimal solution set to NSGA-II has better convergence and scalability. In emergency management and related fields, how to quickly respond to post-disaster emergency needs and reduce disaster losses through the emergency material distribution system of universities is still a challenging research topic in The Korean style. The system must ensure that the number of recipients is maximized, and the recipients have equal opportunities to receive assistance. According to the differences in the characteristics of supply and demand after the disaster, it can be divided into one-time demand and periodic demand, and the two demand pairs have different allocation strategies. On the basis of considering the classification of emergency material supply points, disaster points and emergency materials, the work in [11] takes into account the minimization of emergency material distribution. This allows for effective distribution strategies to be developed on a case-by-case basis. In emergency situations, remote areas have limited resources available, so the main issue that needs to be addressed here is how emergency resources should be allocated among remote areas. The authors in [12] develops an optimal resource and vehicle scheduling models to meet their needs. The integrated model covers the following issues: heterogeneity and dynamics of requirements and route planning of vehicles, as well as a multi-objective model based on the general measures necessary in an emergency. The pre-positioning of emergency supplies is essential to increase the speed of response and mitigate the impact of disasters. To achieve this goal, we chose water wave optimization to design a multi-objective algorithm for the main problem and biogeographic-based optimization for the sub-problem. By designing synthesis, the technique of a multi-layered distributed framework is proposed, which consists of batches of components with hierarchical relationships that can be created from scratch or retrieved from multiple sources over the network.

In some instances, components may include optimization constraints and derive from other components to satisfy optimization constraints. In order to solve the problem of path optimization of vehicle-helicopter combined transportation to cope with large-scale disasters, by minimizing the average waiting time and economic cost of emergency response, a fuzzy multi-objective optimization model with traffic constraints and capacity limitations is established in [13]. In the model presented in [14], the authors take into account that some disaster areas are limited due to the damage of the road network, the ability of means of transport to be limited, and the demand for emergency supplies is uncertain, and only special means of transport are allowed to arrive. Then, the Jingying strategy random neighborhood search (NSGA-SNS-II) is designed to solve the model. In order to improve the efficiency of emergency resource scheduling at multi-field stations, a multi-target emergency material resource scheduling model with non-dominant ranking algorithm is proposed in [15]. In the proposed model, considering the change of casualties, the first goal is the number of effective rescue materials, and the lowest goal is the lowest transportation cost. In the actual material transportation, various modes of transportation and their cost and capacity are the main restrictive factors. The emergency distribution at different sites also has implications for material transport, and these targets and constraints are discussed in the established model in [16]. In an emergency, the design of the distribution network has a great impact on the timely supply of rescue supplies. The supply network has many deficiencies in emergency rescue operations for large-scale events. Therefore, the work in [17] builds a three-level supply network for large emergencies, comprehensively considering the material distribution and transfer station selection, so that the decision makers can grasp the overall situation and formulate a more scientific and planned material distribution plan.

Fuzzy constraints are treated by the most likely method, and multi-targets treat by the constraint method. Minimizing cost and maximizing service level satisfaction are considered as two main objective functions and then developing two competing objective functions in the competition. The developed competitive multi-objective model is solved by using the elastic constraint method, with numerical examples evaluating the power of the proposed method in [18]. A multi-objective allocation and scheduling optimization model that includes reserve points, dispatch points, and emergency rescue materials is established in [19]. The NSGA-II algorithm is proposed to compute the overall layout model, and then to design the binary chromosome-encoded NSGA-II and the corresponding individual repair strategies to address the potential conflict of emergency rescue supplies between multiple dispatch points.

3 Model construction for material distribution

In this section, first we discussion the assumptions made for our proposed model in Sect. 3.1. Various symbols used by the models are presented in Sect. 3.2. The objective function and constraints imposed for building the model are presented in Sect. 3.3.

3.1 Model assumptions

In order to highlight the main characteristics of the logistics system in an emergency, the advanced nature is assumed as follows:

1) Emergency supplies are available with multi-supply points.

2) There are multi-disaster points having a variety of emergency materials.
3) A certain number of emergency material supply points are established to deliver materials to disaster-stricken points.
4) Choose a vehicle from the list of vehicles allocated to the selected supply point only. Number of allocated vehicles is sufficient.
5) The multi-cycle supply point of emergency material demand remains unchanged.
6) The longer the delay in the delivery of materials to the disaster site, the less utility it will have.
7) The distribution of materials between facilities at the same level is not allowed, and the distribution of materials between facilities at different levels is realized by direct distribution.

3.2 Symbol description

The parameters used in our work are as follow.

I: Collection of disaster points, $i = 1, 2, \cdots m, i \in I$;

J: Candidate supply point collection, $j = 1, 2, \cdots n, j \in J$;

T: Relief cycle set, $t = 1, 2, \cdots \tau, t \in T$;

K: Emergency supplies type collection, $k \in K$;

P: The number of selected emergency supply points;

d_{ikt}:t Cycle disaster point i demand for emergency supplies k;

a_k: Unit weight of material k;

b_k: The unit volume of material k;

C_j: The capacity of the supply point j;

W: The maximum load of the vehicle;

V: Maximum capacity of the vehicle;

ζ: The total number of available vehicles;

M: A large number;

u_k: The utility generated by the demand for unit material k being met in the slot period;

V: *The* number of delay periods for the delivery of unit material k to the disaster point $v = 1, 2, \cdots v_{\max}$;

u_{kv}: The utility produced by the delay of demand per unit of material k v cycles. If $v > v_{\max}$ so, then $u_{kv} = 0$.

In this study,

X_i:j is chosen as the supply point as 1, otherwise as 0,$j \in J$;

Y_{ijt}: The disaster point of the t cycle i is denoted as 1 *if* it is delivered by supply point j, otherwise it is 0,$i \in I, j \in J$;

x_{ijkt}: The amount of category K material transported by point j in the t-cycle of the disaster i;

w_{ijktv}: *The* demand for k-type materials at the disaster point i of the i th cycle is delayed by the supply point j the amount of v cycle delivery;

l_{ijkt}: The unmet demand for class k materials at the disaster point of the t-cycle i;

σ_j: The number of available vehicles allocated to supply point j;

s_{jk}: The amount of k-type goods at supply point j.

3.3 Model Building

Based on the above problem description and symbolic definition, the multi-objective dynamic positioning-allocation model established in this paper can be expressed as:

3.3.1 Objective function

Goal 1

$$\max U = \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} u_k x_{ijkt} + \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} \sum_{v=1}^{v_{\max}} u_{kv} x_{ijktv}. \tag{1}$$

Indicates the disaster point i demand utility maximization goal;

Goal 2

$$\min Z \geq \left| z_e - z_f \right|, , \forall\ e\ f\ \ \in I, (e \neq f \tag{2}$$

where,

$$z_i = \frac{\sum_{k \in K} \sum_{t \in T} u_k d_{ikt} - \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} u_k x_{ijkt} + \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} \sum_{v=1}^{v_{\max}} u_{kv} w_{ijktv}}{\sum_{k \in K} \sum_{t \in T} u_k x_{ijkt}}, \forall i \in I. \tag{3}$$

Indicates the goal of fairness in the distribution of goods [20].

3.3.2 Constraints

$$\sum_{j \in J} X_j = p. \tag{4}$$

Indicates the establishment *of* p emergency supply points;

$$\sum_{j \in J} \sigma_j \leq \zeta. \tag{5}$$

Assign constraints to vehicles at each emergency supply point, which must not exceed the total number of available vehicles;

$$Y_{ijt} \leq X_j,\ \forall i \in I,\ j \in J,\ t \in T \tag{6}$$

$$x_{ijkt} \leq M Y_{ijt},\ \forall i \in I,\ j \in J,\ k \in K,\ t \in T \tag{7}$$

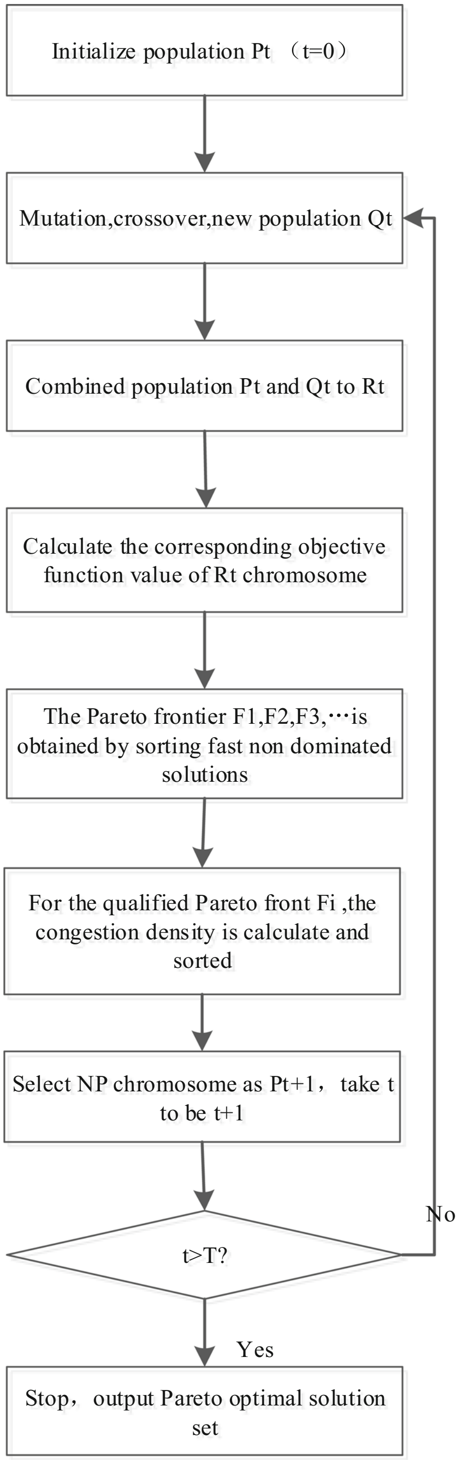

Fig. 1 NSGA-II flowchart

$$w_{ijktv} \leq MY_{ij(t+v)},\ \forall i \in I,\ j \in J,\ k \in K,\ t \in T,\ v = 1, 2 \cdots v_{\max}. \tag{8}$$

Indicates that only emergency supplies are allocated to emergency supplies that have been opened;

$$\sigma_j \leq Ms_{jk},\ \forall j \in J,\ k \in K. \tag{9}$$

Indicates that rescue vehicles are allocated only to selected open emergency supply points;

$$s_{jk} \leq MX_j,\ \forall j \in J,\ k \in K. \tag{10}$$

Indicates that emergency relief supplies are only distributed at selected open emergency supply points;

$$\sum_{k \in K} b_k s_{jk} \leq C_j X_j,\ \forall j \in \left\{ j \middle| j \in J, X_j = 1 \middle| \right\}. \tag{11}$$

The capacity of the distribution of supplies for the selected open emergency supplies supply points;

$$\sum_{j \in J} \left(x_{ijkt} + w_{ijktv} + l_{ijkt} \right) = d_{ikt},\ \forall i \in I,\ k \in K,\ t \in T. \tag{12}$$

Express the equation for the balance of the inflow of relief materials into each disaster point, that is, the sum of the material supplied by the disaster point in the current cycle, the delayed delivery amount and the amount to be satisfied should be equal to the total demand for material k at the disaster point;

$$\sum_{i \in I} \left(x_{ijkt} + w_{ijk(t-v)v} \right) \leq s_{jk},\ \forall j \in J,\ t \in T,\ v = 1, 2 \cdots v_{\max}. \tag{13}$$

Indicates that the outflow of materials from each emergency supply point does not exceed the distribution of its supplies [21];

$$\sum_{i \in I} \sum_{k \in K} a_k \left(x_{ijkt} + w_{ijk(t-v)v} \right) \leq \sigma_j W,\ \forall j \in J,\ t \in T,\ v = 1, 2 \cdots v_{\max}. \tag{14}$$

Indicates the capacity constraint of the rescue vehicle carrying supplies;

$$\sum_{i \in I} \sum_{k \in K} b_k \left(x_{ijkt} + w_{ijk(t-v)v} \right) \leq \sigma_j V,\ \forall j \in J,\ t \in T,\ v = 1, 2 \cdots v_{\max}. \tag{15}$$

Represents the weight constraint of the supplies carried by the rescue vehicle;

$$z_i = \frac{\sum_{k \in K} \sum_{t \in T} u_k d_{ikt} - \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} u_k x_{ijkt} + \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} \sum_{v=1}^{v_{\max}} u_{kv} x_{ijktv}}{\sum_{k \in K} \sum_{t \in T} u_k d_{ikt}},\ \forall i \in I. \tag{16}$$

The satisfaction rate is the satisfaction rate that is effective for the needs of each affected point [22].

$$X_j \in \{0, 1\},\ \forall j \in J \tag{17}$$

$$Y_{ijt} \in \{0, 1\},\ \forall i \in I,\ j \in J,\ t \in T. \tag{18}$$

Equations (17) and (18) are 0–1 integer constraints;

Table 1 Means and variance of the three algorithms

Algorithm	MOP2		MOP3		MOP4		TC4		TC6	
NSGA-II	0.363	0.006	0.456	0.004	0.368	0.018	0.384	0.009	0.384	0.0012
PAES	1.608	0.066	1.362	0.043	1.088	0.063	1.582	0.058	1.184	0.053
SPEA	0.732	0.078	0.891	0.056	0.723	0.018	0.0183	0.000	0.812	0.022

Table 2 the optimal boundary distance and his standard deviation for the three algorithms

Algorithm	MOP2		MOP3		MOP4		TC4		TC6	
NSGA-II	0.002	0.000	0.015	0.000	0.024	0.001	4.523	4.223	0.032	0.001
PAES	0.171	0.002	11.362	12.043	0.123	0.031	0.593	0.532	0.125	0.002
SPEA	0.125	0.004	0.034	0.001	0.043	0.001	7.324	0.432	0.223	0.001

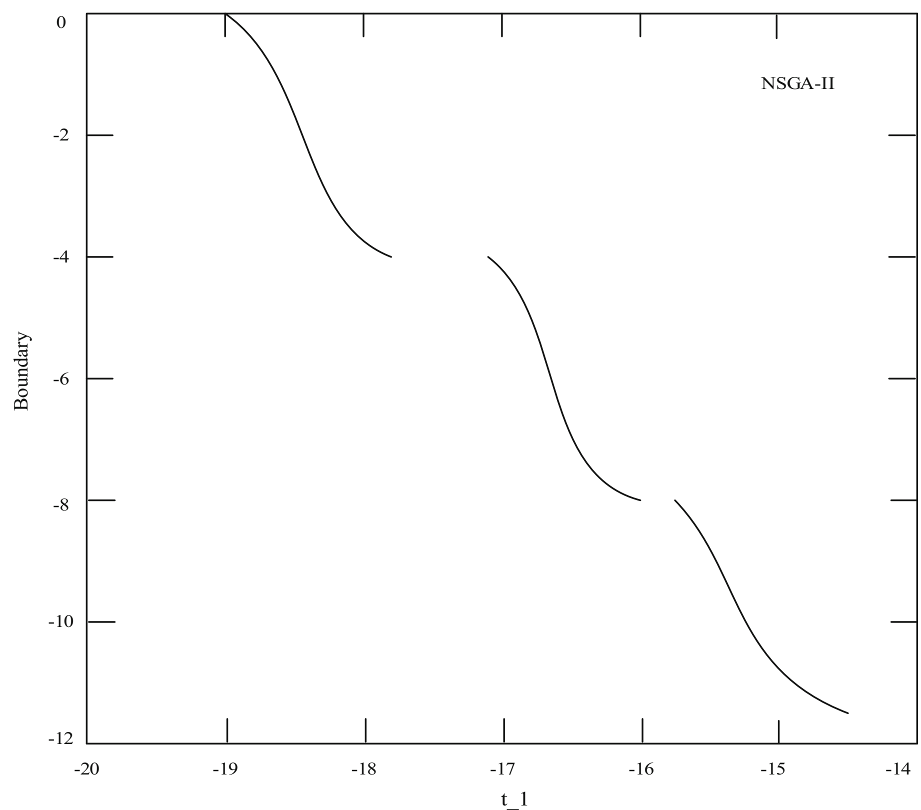

Fig. 2 NSGA-II optimal boundary based on MOP4

$$x_{ijkt}, w_{ijktv}, l_{ijkt}, s_{jk} \geq 0,\ \forall i \in I,\ j \in J,\ k \in K,\ t \in T,\ v = 1, 2 \cdots v_{\max}. \tag{19}$$

Equation (19) represents a non-negative constraint;

$$\sigma_j \geq 0 \text{ is an integer, } \forall j \in J. \tag{20}$$

Equation (20) represents a non-negative integer constraint.

4 Multi-objective optimization genetic algorithm design

4.1 Optimized unconverted solution sorting

The optimized non-dominant solution ordering (NSGA-II) can combine the non-dominated solution sorting mechanism based on crowd density and the cross-variation operation of the genetic algorithm to obtain a better Pareto solution set, which is an algorithm that meets the OLRP solution requirements. Based on the genetic algorithm of non-dominant solution sequencing, the initial population is obtained by initialization P_0, and each chromosome in the initial population corresponds to a distribution

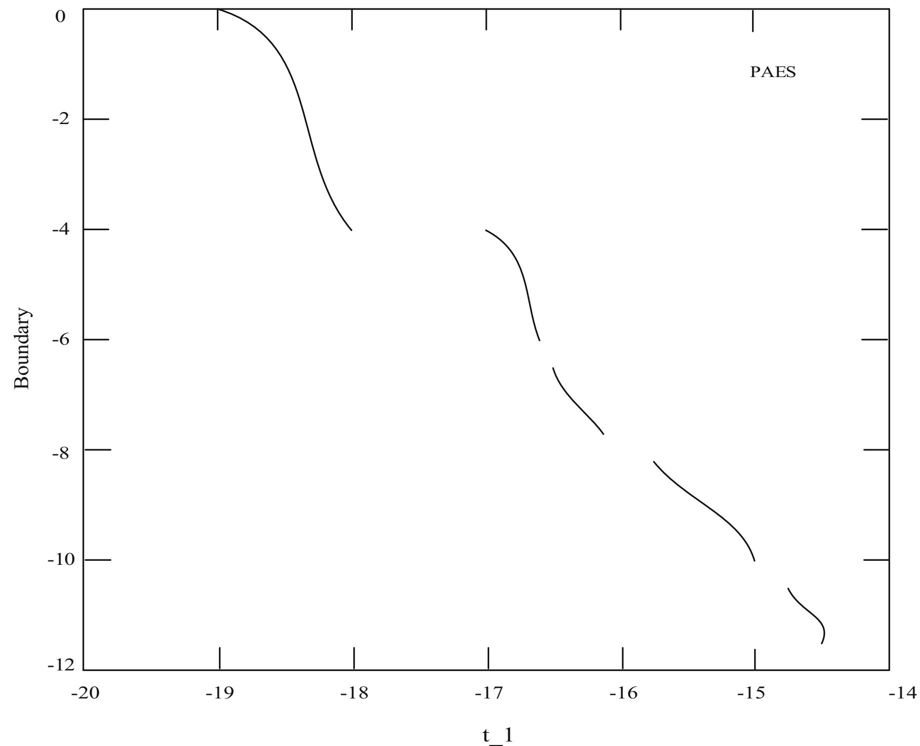

Fig. 3 The PAES optimal boundary based on MOP4

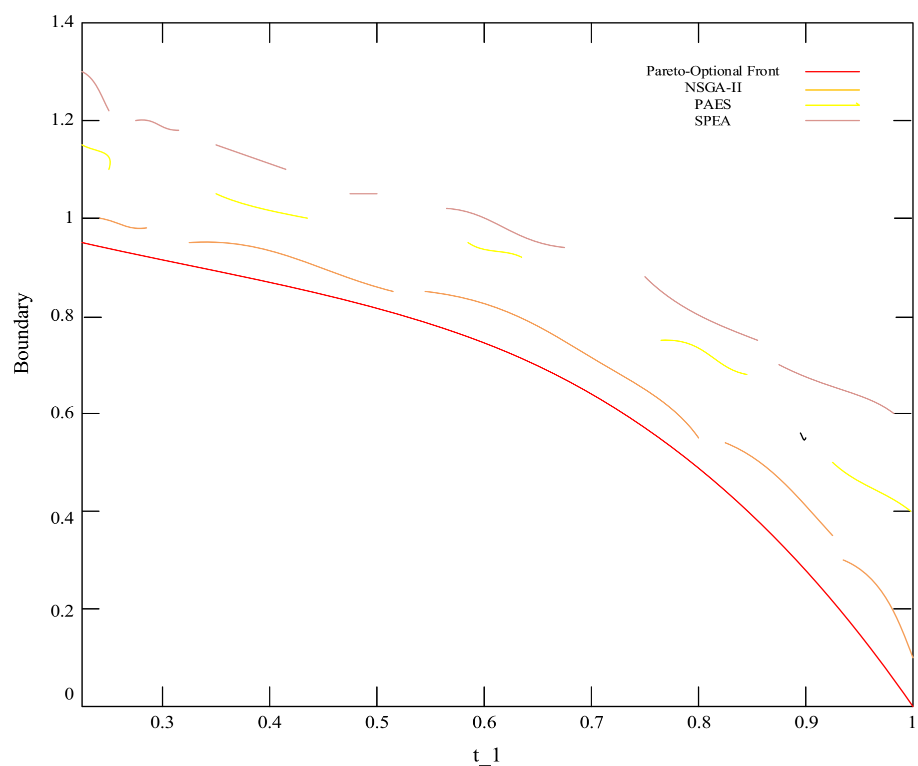

Fig. 4 Using TC6 to compare the optimal boundary obtained by NSGA-II, PAES, and SPEA

Table 3 Capacity of candidate emergency supply points

Candidate emergency supply point number	Facility capacity (tons)
1	80
2	100
3	85
4	90
5	70
6	110

Table 4 Material requirements at the affected sites

Disaster point number	Food (tons)	Daily necessities (tons)
1	95	80
2	82	65
3	100	90
4	80	100
5	90	85
6	65	70
7	105	90
8	75	65
9	80	100
10	100	110

scheme [23]. Order P_1 and Q_1 combine to obtain a population R_1 of 2NP, which is produced by this algorithm to approximate Pareto optimal solution leading level F_1, F_2, F_3,…, and then obtains the quantity by crowd density sorting method NP's chromosomes enter the next generation of chromosome populations P_{l+1}, thus preserving elite individuals from entering the next generation of chromosome populations [24].

4.1.1 Chromosome encoding and initialization

In this paper, the initial chromosomal population is obtained using the method of natural number arrangement encoding, each with three substrings, and its expression is shown in Eq. (21).

$$S_g^l = \{\underbrace{\left(s_{g11}^l, s_{g12}^l, \ldots, s_{g1k}^l\right)}_{s_{g1}^l}, \underbrace{\left(s_{g21}^l, s_{g22}^l, \ldots, s_{g2k}^l\right)}_{s_{g2}^l}, \underbrace{\left(s_{g31}^l, s_{g32}^l, \ldots, s_{g3n}^l\right)}_{s_{g3}^l} \tag{21}$$

where n represents the chromosome; k is the vehicle; l represents the algebra, when l = 0 represents the initial population; g represents the g th chromosome in the population, g = 1, 2,…, NP.

4.1.2 Mutation operations

In this paper, S_g^l the inverted variation method is used to mutate the three substreets.

Step1: Pick two points at random.

Parent = [1 2/3 4 5 6 7 8/9 10];

Step2: Invert the gene site between the two points to get the substring.

Substring = [1 2/8 7 6 5 4 3/9 10].

The variation vector corresponding S_g^l to the mutation is generated by the mutation operation, as shown in U_g^l Eq. (22).

$$U_g^l = \{\underbrace{\left(u_{g11}^l, u_{g12}^l, \ldots, u_{g1k}^l\right)}_{u_{g1}^l}, \underbrace{\left(u_{g21}^l, u_{g22}^l, \ldots, u_{g2k}^l\right)}_{u_{g2}^l}, \underbrace{\left(u_{g31}^l, u_{g32}^l, \ldots, u_{g3n}^l\right)}_{u_{g3}^l}. \tag{22}$$

4.1.3 Cross operation

The test vector is obtained by cross operation V_g^l, where the vector is generated by the two-point intersection method v_{g1}^l and v_{g3}^l the vector is generated by a single-point crossover operation v_{g2}^l. Therefore, the experimental vector V_g^l is expressed in the usable formula [25].

$$\{\underbrace{\left(u_{g11}^l, u_{g12}^l, \ldots, u_{g1k}^l\right)}_{u_{g1}^l}, \underbrace{\left(u_{g21}^l, u_{g22}^l, \ldots, u_{g2k}^l\right)}_{u_{g2}^l}, \underbrace{\left(u_{g31}^l, u_{g32}^l, \ldots, u_{g3n}^l\right)}_{u_{g3}^l}. \tag{23}$$

4.1.4 Select actions

Select the sorting steps:

Step1: Combine the current population X_l with the corresponding experimental vector to V_l form a new population with a R_l scale of $2NP$, and R_l calculate the corresponding target values for each individual.

Step2: Perform a R_l quick non-inferior solution ranking on each individual to get an approximate Pareto optimal solution frontier grade F_1, F_2, F_3.

Step3: The F_i number of individuals in the set is expressed S_i. According to the following equation, the corresponding leading edge grade r is found, and F_r the crowd density of the medium individual is calculated, and the calculated crowd density is arranged in descending order [26].

$$\begin{cases} \sum_{i=1}^{r-1} S_i \le NP \\ \sum_{i=1}^{r} S_i \ge NP \end{cases}. \tag{24}$$

Table 5 Typical Pareto solution

Typical solution	Develop supply points	Number of cycles	The point of the service	Emergency material requirements (tons)		The number of vehicles allocated	Target value 1: U	Target value 2: U
				Foodstuff	Daily necessities			
1	1	1	2,5,9	118	50	4	1308.6	63.7
		2	3,5	36	44			
		3	1,3	35	45			
	2	1	2,4	61	40	8		
		2	1,4,10	129	166			
		3	1,8	94	104			
	3	1	3,6	83	96	8		
		2	3,5	41	48			
		3	5,7,9	149	41			
2	1	1	1,4,7	86	77	5	1306.9	61.6
		2	4	62	23			
		3	5,7	55	103			
	3	1	9	69	25	7		
		2	1,2,3	92	89			
		3	2,3,8	132	55			
	4	1	6,7,10	125	77	8		
		2	3,6,8	81	115			
		3	3	75	28			
3	2	1	5,7,8	154	53	8	1304.9	56.8
		2	1,4,9	131	73			
		3	2,4	71	32			
	3	1	3,6	119	66	7		
		2	5	57	35			
		3	1,5	114	70			
	6	1	10	18	59	5		
		2	2,10	67	92			
		3	3,5	147	27			

Step4: F_1 Selected F_{r-1} individuals and F_r former $NP - \sum_{i=1}^{r-1} S_i$ individuals to enter the next generation X_{t+1}.

4.2 Implementation process

The specific process is shown in the following Fig. 1:

4.3 Evaluation model

Comparing NSGA-II and Pareto Archived Evolution Strategy (PAES), the superiority of the NSGA-II algorithm over emergency allocation of goods can be seen, [27] and the test function is as follows:

MOP2:

$$f_1(x) = 1 - \exp\left(-\sum_{i=1}^{3}\left(x_i - \frac{1}{\sqrt{3}}\right)^2\right) \tag{25}$$

$$f_2(x) = 1 - \exp\left(-\sum_{i=1}^{3}\left(x_i + \frac{1}{\sqrt{3}}\right)^2\right), \ -4 \le x_1, x_2, x_3 \le 4. \tag{26}$$

MOP3:

$$f_1(x) = \left[1 + (A_1 - B_1)^2 + (A_2 - B_2)^2\right] \tag{27}$$

$$f_2(x) = \left[(x+3)^2 + (y+1)^2\right] \tag{28}$$

where:

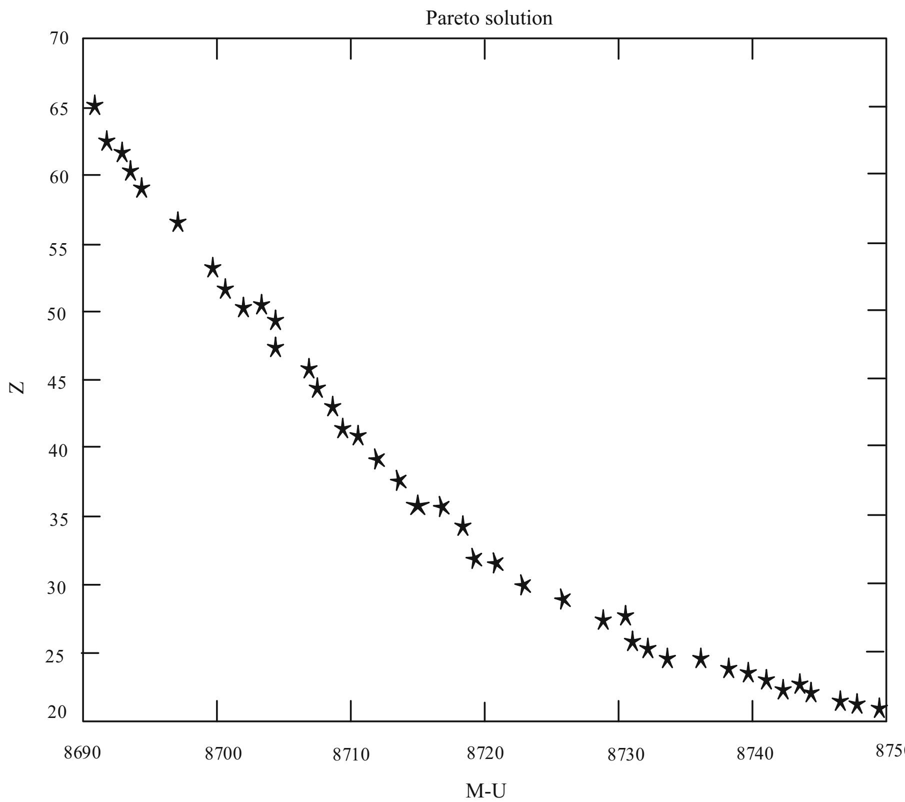

Fig. 5 Pareto Frontier

Table 6 Algorithm performance test

serial number	Population size	Maximum iteration number	Number of different Pareto solutions	Time(s)
1	100	400	53	526.07
2	100	200	41	255.44
3	100	50	30	66.42
4	50	50	13	31.23

$$A_1 = 0.5\sin 1 - 2\cos 1 + \sin 2 - 1.5\cos 2 \tag{29}$$

$$A_1 = 0.5\sin 1 - 2\cos 1 + \sin 2 - 1.5\cos 2 \tag{30}$$

$$B_1 = 0.5\sin x - 2\cos x + \sin y - 1.5\cos y \tag{31}$$

$$B_1 = 0.5\sin x - 2\cos x + \sin y - 1.5\cos y. \tag{32}$$

MOP4:

$$f_1(x) = \sum_{i=1}^{n-1}\left(-10\exp\left(-0.2\sqrt{x_i^2 + x_{i+1}^2}\right)\right) \tag{33}$$

$$f_2(x) = \sum_{i=1}^{n}\left(|x_i|^{0.8} + 5\sin(x_i)^3\right). \tag{34}$$

TC4:

$$f_1(x) = x_1,\ 0 \le x_1 \le 1 \tag{35}$$

$$f_2(x) = g\left(1 - \sqrt{\frac{x_1}{g}}\right),\ -5 \le x_2, \cdots, x_{10} \le 5 \tag{36}$$

Thereinto

$$g(x) = 91 + \sum_{i=2}^{10}\left(x_i^2 - 10\cos(4\pi x_i)\right) \tag{37}$$

TC6:

$$f_1(x) = 1 - \exp(-4x_1)\sin^6(6\pi x_1),\ 0 \le x_i \le 1\ i = 1, \cdots, 10 \tag{38}$$

$$f_2(x) = g\left(1 - \left({}^{f_1}\!/_{g}\right)^2\right). \tag{39}$$

Thereinto

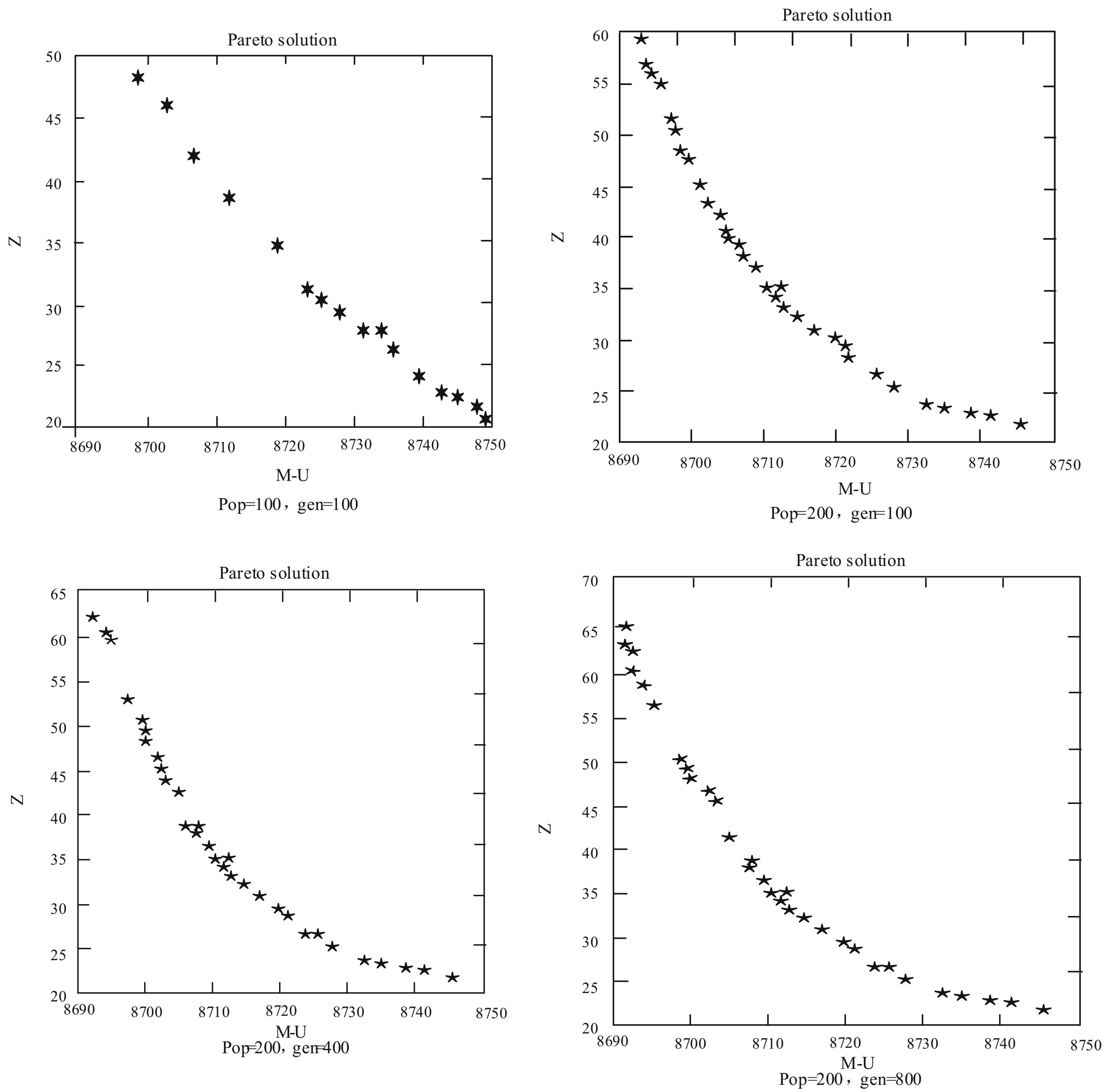

Fig. 6 Pareto front of different studies

$$g(x) = 1 + 9\left(\sum_{i=2}^{10} x_i/9\right)^4. \tag{40}$$

We designed two methods: one based on continuous distance and the other based on average distance. Comparing the first non-dominant layer with the consistent distribution, the corresponding deviation is as follows [28].

$$\Delta = \sum_{i=1}^{|\chi_1|} \frac{\left|d_i - \overline{d}\right|}{|\chi_1|}. \tag{41}$$

Table 1 the difference between the mean and variance obtained by comparison of the three algorithms of NSGA-II, PAES and SPEAΔ.

Table 2 compares the three algorithms of NSGA-II, PAES and SPEA to obtain the distance of Pareto's optimal boundary and its standard deviation.

As shown in Figs. 2, 3 and 4, the Pareto optimal boundary graph obtained by the MOP4 test function shows that the NSGA-II has a better and clearer distribution.

Comparing the above three algorithms with the test function TC6 to obtain their optimal boundary values respectively, specified here g = 3.5, the boundary of NSGA-II is smoother and clearer.

5 Algorithm testing and analysis

5.1 Algorithm parameter settings

The relevant parameters of the multi-objective optimization genetic algorithm are set as follows in Tables 3 and 4:

5.2 Simulation results of the study

To verify the reliability and feasibility of the built model, the present algorithm is programmed to obtain the partial operation results shown in Table 5. The optimal solution distribution is shown in Fig. 5.

The algorithm constructed in this paper can solve multiple supply points and multiple disaster points in a certain period of time, which reflects the reliability and availability of the model. Decision makers can reasonably allocate materials according to the overall situation, reasonably allocate materials for each material demand point, seek fairness, and choose a suitable post-earthquake emergency organization plan on the Pareto front.

5.3 Algorithm performance analysis

We set four examples according on the population size and number of iterations to test the performance of the algorithm. Experimental results are shown in Table 6 and Fig. 6, and from the comparison plots, we can see that the computation time increases with the number of iterations.

As the population size increases and the number of iterations increases, so does the number of Pareto solutions. The distribution is also more uniform [25].

6 Conclusions

After the emergency occurs, the selection of the optimal emergency rescue materials distribution route is the primary problem for the emergency decision makers. The allocation of resources shall not exceed the resource reserve, and the demand of materials obtained at each disaster point is the main goal of the optimization model. We complete the modeling for two targets and multiple constraints, and give the optimized algorithm for solving it. The independent solution-based sorting algorithm is suitable for large-scale emergency material distribution design routes. The site selection is reasonable, and can provide various decision-making methods, have a good adaptability to the emergency situation, greatly optimize the emergency materials distribution planning system, and reduce the difficulty of emergency materials distribution. The experimental results justify that the proposed model is efficient as compared to the existing ones and can be used for a wide range of applications that require optimal allocation of material dispatch for emergency events.

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Declarations

Conflict of interest The authors declared that they have no conflict of interest regarding this work.

Data availability The experimental data used to support the findings of this study are available from the corresponding author upon request.

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