SCHEDULING OPTIMIZATION OF MULTI-TARGET EMERGENCY SUPPLIES FOR MULTI-LOCATION OUTBREAK

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Received February 2023; accepted April 2023

ABSTRACT. Major epidemics break out at the same time in many places, and in the process of response, we are faced with the problem of coordinated assistance between different material aid points. Considering the dual objectives of minimizing unmet needs and minimizing maximum arrival time in emergency assistance in multi-location, a multi-objective nonlinear programming model for collaborative assistance in multi-location outbreak is established and an improved fast non-dominated sorting genetic algorithm (NSGA-II) was used to solve the mode. Finally, a numerical experiment was carried out against the background of simultaneous outbreaks in multiple places. The results show that the aid effect of the nearest aid distance severity-first strategy was better than that of the shortest aid distance first strategy.

Keywords: Multi-location outbreak, Multi-objective coordination, Emergency material assistance, Aid coordination

1. Introduction. In recent years, the COVID-19 pandemic has caused severe shortages of emergency response supplies [1]. It is particularly important to optimize the distribution of emergency supplies and meet the demand for supplies during the epidemic. The allocation of emergency supplies refers to the rational allocation of various emergency supplies from different emergency aid supply points to different demand points in different epidemic areas in the shortest possible time after the outbreak, according to the demand level of the epidemic area [2]. In order to solve the imbalance between the scarcity of materials and the excess demand of materials in disaster areas, relevant scholars at home and abroad have studied the distribution of emergency materials from different perspectives: simulation analysis is used to study the optimal allocation of emergency aid materials [3], use big data to analyze dynamic demand and distribution of materials [4,5], and the dispatch of emergency relief materials is studied by using complex network technology [6] and location of emergency supplies [7]. In the research of mathematical modeling and algorithm optimization [8,9], in order to realize the optimal distribution of supply points and demand points, the viewpoints of timeliness and fairness should be considered in the process of emergency supplies distribution. However, in the actual process of emergency supplies distribution, there will be some problems such as asymmetric supply and demand information and inaccurate demand prediction [10,11], which will lead to problems such as surplus or shortage of emergency relief materials, increase in distribution costs and decrease in relief effectiveness.

In order to effectively solve the problems of redundancy, waste, low efficiency and high cost of emergency relief supplies allocation, an improved NSGA-II was proposed in this paper, and the allocation and scheduling model of emergency relief supplies was

DOI: 10.24507/icicel.17.11.1253

constructed. The effects of different strategies were analyzed and compared considering the degree of epidemic urgency and distribution distance. It provides scientific basis for the accurate allocation of emergency relief materials.

The overall structure of this paper is as follows. In Section 2, the mathematical model of multi-objective distribution of epidemic emergency supplies is established and the detailed problem description is summarized. In Section 3, an improved algorithm of NSGA-II in emergency aid is proposed. Section 4 verifies the correctness of the algorithm and the fairness of the distribution of disaster relief materials through the simulation model of the distribution of emergency relief materials in multiple epidemic areas. Finally, Section 5 concludes the paper.

2. Problem Description and Model Settings.

2.1. **Problem description.** The epidemic is fast transmission and strong concealment, so it is easy to present multiple outbreaks and spread epidemic. As a result, many regions need to take emergency prevention and control measures such as lockdown at the same time, thus becoming multiple demand points for emergency supplies. The initial emergency response centers were insufficient to meet the needs of the affected areas, resulting in a shortage of emergency resources in the affected areas. In order to solve these problems, it is necessary to consider the uncertainty of emergencies and the dynamic and timely nature of aid plans in the process of emergency decision-making. Consider two objectives.

1) Unmet demand, which reflects the efficiency of emergency aid. In the aid process, aid supplies failed to fully meet all the needs of the epidemic area after arrived at the demand point. The emergency resource dispatch center instructs other supply points to send assistance teams to meet the needs of the demand points in the affected area.

2) Min max arrival time, which reflects the effect of emergency aid logistics. After the outbreak, the arrival time of emergency supplies will affect the transmission speed of the epidemic. The length of time it takes to arrive will affect how quickly the disease spreads. Different emergency assistance strategies at the supply point can produce different arrival times [10], as shown in Figure 1. In Figure 1, A and B are the supply points, and nodes 1, 2 and 3 are the outbreak sites. The triangle above the supply point node is the quantity of material reserve, and the triangle above the demand point node is the quantity of demand. In this example, the quantity of material is equal to the quantity of demand. The number on the line between the supply point and the demand point represents the



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(a) The closest assistance is from the priority severity route

(b) Priority routes for the shortest distance of outbreak severity

FIGURE 1. Relationship between epidemic assistance strategy and arrival time

distance, and the arrows in (a) and (b) represent the sequence of emergency logistics scheduling after the emergency strategy is adopted. It is assumed that the aid driving speed is 1 unit. Figure 1(a) shows the severity-priority scenario for taking the closest aid. In the scheduling scheme, the time taken by different routes is (2, 2, 2, 3). Figure 1(b) shows the scenario with the shortest distance priority for epidemic severity. The time taken by different routes in the scheduling scheme is (2, 3, 4, 2). It can be seen that different emergency scheduling policies have different effects.

2.2. Model settings. Suppose there are *n* material supply points $I, S = \{s_1, s_2, \ldots, s_n\}$, which need to respond to the emergency needs of *m* demand points *j* in the epidemic area, $G = \{g_1, g_2, \ldots, g_m\}$. For $\forall s_i \in S$, there is a reserve quantity of emergency anti-epidemic materials $h_i, i \in \{1, 2, \ldots, n\}$, where $h_i \geq 0$ is a non-negative integer, indicating the reserve quantity s_i of emergency anti-epidemic materials h_i at the emergency demand station.

For $\forall g_j \in G$, an aid needs d_j , $j \in \{1, 2, ..., m\}$, where $d_j \geq 0$ is an non-negative integer, representing the need for anti-epidemic supplies d_j of emergency demand station. There is a corresponding emergency response time requirement for $\forall g_j \in G$.

 $\delta_j \in \Delta = \{\delta_1, \delta_2, \dots, \delta_m\}$ represents the $\delta_j > 0$ (positive integer) time in which emergency assistance must be transported to the point of need g_j . $z_{s_ig_j}$ is a 0-1 decision variable, representing the relationship between the actual arrival time t_{ij} from supply point s_i to demand point g_j and the limited time of demand point. If $t_{ij} \leq \pi_j$, $z_{s_ig_j} = 1$; otherwise, $z_{s_ig_j} = 0$.

For any given s_i to g_j there is an actual aid contribution w_{ij} , $i \in \{1, 2, ..., n\}$, $j \in \{1, 2, ..., m\}$, where w_{ij} is a non-negative integer and belongs to $[0, h_i]$, representing the actual contribution of aid supplies from supply point s_i to demand point g_j . Obviously, $w_{ij} = 0$ means that supply point s_i is not responding to the emergency request of demand point g_j .

Therefore, considering the distribution of emergency supplies from multiple supply points and multiple demand points, the problem is to simultaneously distribute aid supplies to multiple supply points s_1, s_2, \ldots, s_n for multiple demand points g_1, g_2, \ldots, g_m of the epidemic area, namely, the following two objective optimization problems.

(i) Minimize the unmet requirement f_1 :

$$Minf_{1}(W) = \sum_{j=1}^{m} \left(d_{j} - z_{s_{i}g_{j}} \sum_{i=1}^{n} w_{ij} \right)$$
(1)

Objective function (1) is to minimize unmet demand. The first term on the right side of the equal sign is the estimated demand, and the second term is the contribution of the supply point in the case of assistance.

(ii) Minimize the maximum arrival time f_2 :

$$Minf_2(T) = Max\left(\sum_{i=1}^n \sum_{j=1}^m \left(t_{ij} z_{s_i g_j}\right)\right)$$
(2)

Objective function (2) is to minimize the maximum arrival time of aid. Time t_{ij} on the right side of the equation equals s_{ij}/v_{ij} , s_{ij} represents the distance from supply point *i* to demand point *j*, and v_{ij} is the speed. Constrains:

s.t.
$$\sum_{i=1}^{n} w_{ij} \ge d_j, \quad 1 \le j \le m$$
(3)

$$\sum_{i=1}^{n} w_{ij} \le h_i, \quad 1 \le i \le n \tag{4}$$

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$$t_{ij} \le \delta_j, \quad 1 \le i \le n, \ 1 \le j \le m \tag{5}$$

$$z_{s_i g_j} \in \{0, 1\}, \quad 1 \le i \le n, \ 1 \le j \le m$$
 (6)

All constraints are satisfied simultaneously. Constraint (3) requires the contribution of supplies to the emergency response should be greater than or equal to the demand of the epidemic area; Constraint (4) requires the contribution of supply points to emergency supplies should be less than or equal to the reserve of supply points to emergency supplies; Constraint (5) requires the arrival time of aid from the supply point to the demand point is less than or equal to the demand time of the epidemic area; Constraint (6) requires the value of the decision variable can only be 0 or 1.

3. Algorithm Design. On the basis of NSGA-II algorithm, the algorithm was improved to complete the generation of the initial solution of the algorithm with heuristic rules, to ensure the feasibility of the solution by designing the fitness function and population repair, and to improve the operator to maintain the optimality of the solution in the process of algorithm generation selection [11]. Figure 2 shows the main process of NSGA-II algorithm.



FIGURE 2. The calculation flow of NSGA-II algorithm

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3.1. Coding rules and initial population determination. In order to determine the sequence and arrival time of multi-target emergency supplies from supply points to demand points, the solution is a sequence composed of aid routes. Figure 3 shows the coding rules of chromosomes and the scheduling scheme of how to convert them into aid routes. The sequence of chromosomes is [3, 1, 2, 5, 4, 1, 1, 3, 3, 2] and the corresponding scheduling scheme is $(R_{31}, R_{11}, R_{23}, R_{53}, R_{42})$. The variable R_{ij} represents the priority order of aid routes from supply point *i* to demand point *j*. [3, 1, 2, 5, 4] represents the contribution of the supply point. [1, 1, 3, 3, 2] represents the speed at which the demand point is reached. According to the coding generation mode of the aid program, the heuristic rule algorithm is used to solve the initial solution, which is the arrangement of the rescue group, that is, the aid program. The aid program produces different results according to different rules, such as the nearest principle aid, and the severity of the epidemic aid.



FIGURE 3. Chromosome mapping for rescue scheduling scheme

3.2. Fitness assessment and rules for population restoration. Fitness evaluation is the criterion for selecting chromosomes, which is mainly determined by objective function and constraint conditions. In general, the larger the fitness, the better. The target variable in this model is to minimize the unmet needs of aid time and demand points, and the value of this fitness function changes inversely with the target function. Let the fitness function be $f_h = [TC(t)]^{-1}$, then the larger f_h is, the better the performance of f_h is, and the closer the corresponding solution is to the optimal solution.

3.3. **Operator selection process.** According to the calculation results of fast nondominated sorting and the size of the crowding degree operator, the tournament operator is used for selection. The tournament operator randomly selects individuals in the population for comparison, using the relative value of the fitness value as the criterion to generate the next generation of parents from individuals with the best fitness value. This selection method is conducive to individuals with better fitness values having a better chance of survival. Tournament selection can to some extent avoid premature convergence and convergence stagnation phenomena.

3.4. Crossover and mutation operators. Crossover operator for selection probability for p_c by populations of crossover, random set of individual in the population and crossover position, make the matching of individual exchange position, delete cross section information in the chromosomes of the parent generation, and will be another cross part of the chromosome complement to delete some information of the parent generation. The mutation operator mutates the crossed population with a probabilistic rate of p_m . To preserve the complete arrangement of the rescue route and satisfy the constraint conditions, a chromosome is randomly chosen as the mutation chromosome. Two random numbers are generated to indicate the positions of the mutation genes. The genes at these positions are swapped to create a new chromosome. The chromosome is then evaluated for constraint conditions. If it does not violate the constraints, it is considered a valid offspring. Otherwise, the generation is re-selected.

4. Numerical Experiments.

4.1. Experiment design. In this section, numerical experiments are carried out against the background of multi-point outbreak in a certain region, so as to illustrate the effectiveness of the model and algorithm and the effect of different strategies on scheduling schemes. In the numerical experiment scenario, the emergency resource control center estimated the demand quantity of the epidemic area based on the real-time monitoring system of the number of patients in the epidemic area. Emergency supplies include medical protective masks, surgical masks, common masks, disposable medical protective suits, etc. The quantity of supplies at each supply point and the quantity required by each epidemic area is an integer.

Algorithm parameters are set as follows: in NSGA-II algorithm, population size N = 100, crossover probability $p_c = 0.9$, mutation probability $p_m = 0.15$, individuals are selected into the mating pool by tournament method, crossover, mutation and other genetic operation methods. The maximum generation of the above algorithm is ITER = 500.

4.2. Analysis of experimental results. The number of epidemic patients is relatively limited, and the supply at the supply point is greater than the demand at the demand point in the epidemic area. Therefore, the experiment design should ensure that the supply at the supply point equals the demand at the demand point. According to the aid strategy of emergency supplies given in Part (2) of 2.1, the problem was solved by using two strategies: the closest aid distance severity-first strategy (strategy 1) and the shortest aid distance first strategy (strategy 2), namely, different aid scheduling schemes (aid route ranking). Table 1 shows the number and distance of different supply points and demand points after the outbreak in a certain region, and in parentheses are material demand and reserve quantity of demand point and supply point.

$j \langle i \ (\mathrm{km}) \rangle$	s_1 (1600)	s_2 (1500)	s_3 (1300)	s_4 (1400)
$g_1 (1200)$	127	8	190	155
g_2 (1300)	200	125	170	160
$g_3 (1400)$	166	260	175	180

TABLE 1. Distance between supply point and demand point

In order to analyze the aid effect of emergency prevention and control materials under different strategies after the outbreak of the epidemic, the NSGA-II algorithm was used to compare the number of supply points and demand points, the demand for emergency prevention and control materials and the amount of reserves, respectively, when the iterations were 200 times and 500 times. Results of strategy 1 and strategy 2 under three Pareto optimal optimization schemes are shown in Table 2.

According to the numerical parameters set in the example (as shown in Table 1), the model of emergency anti-epidemic material assistance in multi-location outbreak was



(b) The shortest epidemic severity-first strategy

FIGURE 4. Pareto optimal frontier under two strategies

solved, and the Pareto optimal solution set was obtained by the running program, as shown in Figure 4. List the solutions of emergency material aid corresponding to three representative points on Pareto optimal frontier, including the optimal point of unmet needs, the comprehensive optimal ideal point and the optimal point of aid time, respectively.

Observation 1: In the case of multiple iterations, the strategy focusing on epidemic severity can better meet the demand for epidemic prevention materials than the strategy focusing on distance, and reduce to the level of meeting the demand. Although the delivery time is relatively longer, ideal point works better.

As shown in Figure 4 "Pareto Optimal Frontier", this algorithm has good convergence and can obtain a good Pareto frontier. According to the actual aid situation of emergency supplies, when the demand point is more focused on meeting the demand, the optimal plan of unmet demand can be selected, that is, the point on the upper left in Figure 4. When the demand point focuses more on the shortest aid arrival time, the plan with the shortest aid arrival time can be selected, that is, the point in the lower right of Figure 4. By integrating the above two optimal situations, the ideal point is the most comprehensive advantage. If the threshold value of a certain time or demand is given, all feasible solutions superior to this time or demand can be found on the Pareto optimal frontier (T = 5.28).

Observation 2: Among the integrated optimal ideal points, the strategy that emphasizes the severity of the epidemic increased significantly in terms of the superiority of material allocation with the increase of the number of iterations, but had little disadvantage in terms of delivery time.

Table 2 shows the results of the solutions of Pareto optimal ideal points under the two strategies in the case of 500 iterations. It can be seen that when the algorithm is iterated 200 and 500 times, the optimal scheduling scheme of emergency prevention and control material assistance does not change. The objective function results are improved. According to parameter settings in Table 1, the optimal scheduling schemes generated by strategy 1 and strategy 2 are $(R_{21}, R_{11}, R_{32}, R_{42}, R_{13})$ and $(R_{22}, R_{32}, R_{11}, R_{13}, R_{43})$. When the generation is selected for 500 times, the optimal solution of strategy 1 is (-479.6, 5.28), and the optimal solution of strategy 2 is (-2.88, 8.31). Strategy 2 only has a slight advantage in the result of shortest aid arrival time in objective function 2, and strategy 1 has a better scheduling scheme.

Optimal aid route R_{ij}	Numerical results					Objective function		
	(500 iterations)					(500 iterations)		
	Contribution		s_1	s_2	s_3	s_4	Unmet	Maximum
Stratogy 1							demand	arrival time
(P, P, P, P, P)		g_1	1220	420	0	0		
$(R_{21}, R_{11}, R_{32}, R_{42}, R_{13})$	w_{ij}	g_2	0	0	400	390	-479.6	5.28
		g_3	410	0	0	0		
	Contribution		s_1	s_2	s_3	s_4	Unmet	Maximum
Stratogy 2							demand	arrival time
(P, P, P, P, P)	w_{ij}	g_1	380	0	390	0		
$(R_{22}, R_{32}, R_{11}, R_{13}, R_{43})$		g_2	0	400	635	0	-2.88	8.31
	-	g_3	0	0	0	420		

TABLE 2. Solutions corresponding to optimal strategy points on Pareto optimal frontier

5. Conclusions. The aid of multi-target emergency response materials was studied against the background of multi-location outbreak and multi-supply point coordinated aid. The multi-objective model was constructed and solved by NSGA-II algorithm. Finally, experiments are carried out against the background of multi-point outbreak of the epidemic to prove the rationality and effectiveness of the model and algorithm. The following conclusions are drawn: reasonable allocation of emergency resource dispatching centers has a better effect on aid dispatching. In the case that multiple epidemic areas need aid at the same time, the effect of the nearest aid priority strategy is better than that of the shortest aid priority strategy. In the future research, the influence of factors such as the type of aid goods and the speed of aid on the aid effect can be further discussed.

Acknowledgment. This research is supported by the General Project of National Natural Science Foundation of China (72274030, 71874024).

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