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FUZZY MULTI-OBJECTIVE OPTIMIZATION OF JOINT TRANSPORTATION FOR EMERGENCY SUPPLIES

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Abstract. *In order to solve the routing optimization problem of vehicle-helicopter joint transportation in response to large-scale disasters, by minimizing the average waiting time and the economic cost of emergency response, this paper establishes a fuzzy multi-objective optimization model with traffic constraints and capacity limits. In the model, we consider some disaster areas only allow special transport tools to arrive because of the damage of the road network, the transportation tools have capacity restrictions and the emergency supplies demands are uncertain. Then, a non dominated sorting genetic algorithm-stochastic neighborhood search with elitism strategy (NSGA-SNS-II) is designed to solve the model. Finally, a case study verifies the effectiveness of the optimization model and the algorithm. The model and the algorithm can provide relief supplies transportation plans for a specific disaster response situation.*

Keywords: Traffic constraint, Capacity limits, Fuzzy demands, Multi-objective optimization, Vehicle-helicopter joint transportation

1. Introduction.

In recent years, large-scale disasters such as Katrina hurricane in 2005, and Wenchuan earthquake in 2008 have caused huge deaths and property loss. The occurrence of large-scale natural disasters often leads to different levels of obstruction or even interruption of the roads, which affect the rescue operation seriously. With the requirements of emergency response level and rescue urgency requirements, the use of vehicle-helicopter for emergency supplies transportation has become an increasingly important way in disaster relief logistics [1].

The disasters caused by roads blocked and roads interrupted make a single rescue tool difficult to carry out the relief in isolated disaster areas. Therefore, Fikar et al. [2] designed a decision support system (DSS) based on simulation and optimization to facilitate disaster rescue coordination between privates and rescue organizations. Based on the key issue that transportation coordinated planning for time limited global tasks in emergency decision-making problems, Zhou et al. [3] proposed a novel multi-agent coordinated planning approach for agents in the system to handle the coordination needs of durative actions and global deadlines. However, these systems and methods cannot meet the requirements of the large-scale problems. Recently, concerning with the problem of the 'helicopters and vehicles' intermodal transportation of medical supplies in response to large-scale disasters, Ruan et al. [4] presented two balanced clustering methods for selecting emergency distribution centers and assigning medical aid areas, formulated a multimodal transport routes optimization model which is based on the clustering and the transfer time, and

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developed corresponding heuristic algorithms of the proposed clustering-based methods. However, it did not make full use of the remaining capacities of the helicopters to assist the vehicles with the rescue of the general affected areas, and the intermodal transport was phased rather than the mixed intermodal transport at the same time, the relief time of the two phases was limited.

After the large-scale disasters, we usually take helicopters and vehicles as two important rescue tools for emergency supplies transportation. Because the key roads to the disaster areas are blocked or even interrupted, it will take some time to clear the roads, causing some isolated disasters emergency demands difficult to meet with vehicles in a short time, so we can only depend on helicopters which have strong mobility and little road capacity limits for transportation. Parts of the disaster areas have traffic constraints, while other common disaster areas' emergency supplies demands will be met by the joint rescue of helicopters' remaining capacity and vehicles, as is shown in Figure 1 (ODAs mean ordinary disaster areas, IDAs mean isolated disaster areas, and LCDH means large collecting and distributing hub). Helicopters are only involved in the isolated disaster areas' emergency supplies transportation in previous studies.

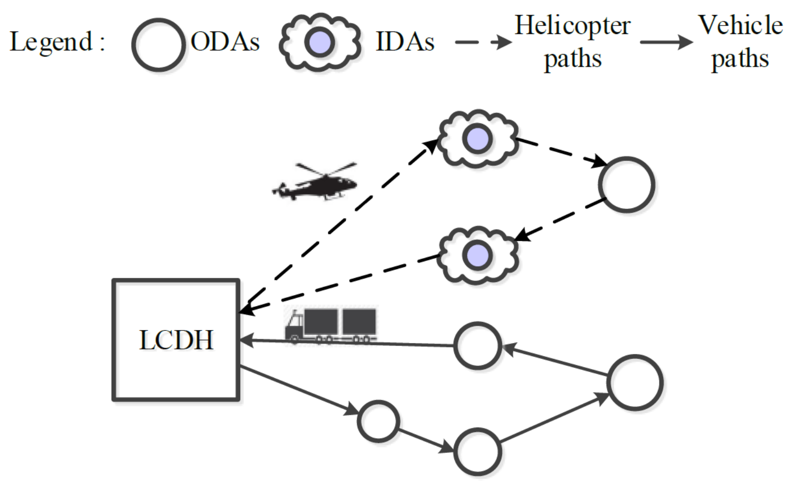

FIGURE 1. The joint transportation procedure of "helicopter + vehicle"

2. **Formulation.** We use complete digraph $G = (V, A)$ to represent the whole network of emergency transportation supplies. $V = \{0, 1, 2, \ldots, num\}$ represents a set of areas, and $\{0\}$ represents the emergency supplies transportation center; $V' = V/\{0\}$ represents the collection of all disaster areas and V'_c represents the collection of disaster areas with traffic constraints; $A = \{(i, j)|i, j \in V, i \neq j\}$ represents the arcs collection of the emergency transportation network; $K = K_1 \cup K_2$ represents the collection of all the capacity, $K_1 = \{k|1, 2, \ldots, k_1\}$ represents the collection of helicopters and $K_2 = \{k|k_1+1, k_1+2, \ldots, k_1+k_2\}$ represents the collection of vehicles. Q_k represents maximum capacity of rescue tool k; v_k represents average speed of rescue tool k; d_{ij} represents length of arc(i, j) and $d_{ij} = d_{ji}$, $\forall i, j \in V$; $\tilde{D}_i$ represents the emergency supplies demand of the disaster area i, which can be expressed by triangular fuzzy numbers $(\alpha_i, \beta_i, \gamma_i)$; C_k, transportation cost of rescue tool k per unit distance; N_k represents the sub-paths collection of rescue tool k; t^n_{ik} represents the time when rescue tool k arrives at area i of sub-path n, t^n_{0k} represents the time when rescue tool k leaves the transportation center of sub-path n, $t^n_{m+1,k}$ represents the time when rescue tool k returns to the transportation center of sub-path n; s_i represents the service time at disaster area i; c_k represents the fixed operating cost of rescue tool k, including the costs of aircraft transfer, route security and alternate airport.

Because the demand of each disaster emergency supplies is fuzzy, let $\tilde{D}_j = (\alpha_j, \beta_j, \gamma_j)$ represents the quantity of the emergency supplies demand for a given disaster area j. We assume that the total transportation quantity of rescue tool k is $D_m^k = \sum_{j=1}^m D_j$, and the remaining load quantity is $\Delta\tilde{Q}_k = Q_k - \tilde{D}_m^k$ after rescue tool k services m disaster areas. ΔQ_k is also a fuzzy number.

$$\Delta\tilde{Q}_k = (\Delta q_{1,k}, \Delta q_{2,k}, \Delta q_{3,k}) = \left(Q_k - \sum_{j=1}^m \gamma_j, Q_k - \sum_{j=1}^m \beta_j, Q_k - \sum_{j=1}^m \alpha_j\right) \tag{1}$$

Then the possibility of the next area's demand is less than the rescue tool's remaining transportation capacity being

$$\begin{aligned} P &= Cr\left\{\tilde{D}_{m+1} \le \Delta\tilde{Q}_k\right\} \\ &= Cr\left\{(\alpha_{m+1} - \Delta q_{3,k}, \beta_{m+1} - \Delta q_{2,k}, \gamma_{m+1} - \Delta q_{1,k}) \le 0\right\} \\ &= \begin{cases} 0, & \alpha_{m+1} \ge \Delta q_{3,k} \\ \dfrac{\Delta q_{3,k} - \alpha_{m+1}}{2 \cdot (\Delta q_{3,k} - \alpha_{m+1} - \Delta q_{2,k} + \beta_{m+1})}, & \alpha_{m+1} < \Delta q_{3,k},\ \beta_{m+1} > \Delta q_{2,k} \\ \dfrac{\gamma_{m+1} - \Delta q_{1,k} - 2 \cdot (\beta_{m+1} - \Delta q_{2,k})}{2 \cdot (\Delta q_{2,k} - \beta_{m+1} + \gamma_{m+1} - \Delta q_{1,k})}, & \beta_{m+1} \le \Delta q_{2,k},\ \gamma_{m+1} > \Delta q_{1,k} \\ 1, & \gamma_{m+1} \le \Delta q_{1,k} \end{cases} \end{aligned} \tag{2}$$

The optimal scheduling model of the emergency supplies is as follows:

$$Min\ f_1 = \sum_{k\in K}\sum_{n\in N_k}\sum_{i\in V'} t_{ik}^n y_{ik}^n \Big/ num \tag{3}$$

$$Min\ f_2 = \sum_{k\in K}\sum_{n\in N_k}\sum_{(i,j)\in A} d_{ij} x_{ijk}^n C_k + \sum_{k\in K}\sum_{n\in N_k} c_k \tag{4}$$

$$s.t. \quad \sum_{i\in V} x_{ijk}^n = \sum_{i\in V} x_{ijk}^n, \quad \forall j \in V,\ k \in K,\ n \in N_k \tag{5}$$

$$\sum_{k\in K}\sum_{n\in N_k}\sum_{i\in V} x_{ijk}^n = 1, \quad \forall j \in V' \tag{6}$$

$$\sum_{k\in K_1}\sum_{n\in N_k}\sum_{i\in V} x_{ijk}^n = 1, \quad \forall j \in V_c' \tag{7}$$

$$Pos\left\{\sum_{i\in V}\sum_{j\in V'} x_{ijk}^n \tilde{D}_j \le Q_k\right\} \ge \lambda, \quad \forall k \in K,\ n \in N_k \tag{8}$$

$$\sum_{n\in N_k}\sum_{j\in V'} x_{0jk}^n = \sum_{n\in N_k}\sum_{j\in V'} x_{j0k}^n, \quad \forall k \in K \tag{9}$$

$$t_{ik}^n + d_{ij}/v_k + s_i - t_{jk}^n \le \left(1 - x_{ijk}^n\right) M, \quad \forall i, j \in V,\ k \in K,\ n \in N_k \tag{10}$$

$$t_{0k}^{n+1} = t_{m+1,k}^n, \quad \forall k \in K,\ n \in N_k \tag{11}$$

$$x_{ijk}^n + x_{jik}^n \le 1, \quad \forall i, j \in V,\ k \in K,\ n \in N_k \tag{12}$$

$$x_{ijk}^n \left(1 - x_{ijk}^n\right) = 0, \quad \forall i, j \in V,\ k \in K,\ n \in N_k \tag{13}$$

$$y_{ik}^n \left(1 - y_{ik}^n\right) = 0, \quad \forall i \in V',\ k \in K,\ n \in N_k \tag{14}$$

Objects (3) and (4) represent our goal is to minimize the average waiting time of emergency supplies delivering to the disaster areas and to minimize the total scheduling cost of all the rescue tools including the dispatch costs of all the rescue tools and the transportation costs. Constraints (5) guarantee that the rescue tools which arrive at the disaster area must leave from the area; constraints (6) guarantee that each disaster area can only be visited once by the rescue tool; constraints (7) guarantee that the disaster area with traffic constraints can only be visited once by the helicopter; constraints (8) relate the possibility of rescue tool k's total loading is no more than Q_k and ensure that it should be in the confidence interval; constraints (9) ensure that each rescue tool leaves from the transportation center and returns to the transportation center finally; in constraints (10) M represents a positive infinite number, and the constraints represent the calculation relationship of the time in the path of the disaster areas. Constraints (11) guarantee that the time of rescue tool k returning to the transportation center in sub-path n is equal to the time when rescue tool k leaves to the transportation center in sub-path $n + 1$, and this reflects the repeated use of the rescue tools and ensures the operation time of rescue tool k is increasing; constraints (12) eliminate the loop paths. Finally, constraints (13) and (14) define the types and ranges of variables.

3. **Solution Method.** We use the non-dominated sorting genetic algorithm with elitism strategy (NSGA-II) to solve the problem. Besides, based on this algorithm, we develop non dominated sorting genetic algorithm-stochastic neighborhood search with elitism strategy (NSGA-SNS-II), in which initial solution generation and stochastic neighborhood search strategy are improved.

3.1. **Initialization.** We solve the distribution problems with real-coded NSGA-II. It is supposed that there are 1 helicopter, 2 vehicles, 12 disaster areas, and the disaster areas of numbered 1, 3 have traffic constraints. Each raw of chromosomes, which represents a rescue tool, carries the numbers of disaster areas, and in order to ensure the right of the constraint (8), the isolated disaster areas can only be assigned to the helicopter. Figure 2 shows a reasonable way of coding. In addition, each rescue tool may need to operate distribution of multiple sub-paths, and it is necessary to divide sub-paths according to the maximum load of rescue tool k when decoding, for example, the sub-paths of Vehicle2 may be 0-8-9-10-0 and 0-11-12-0.

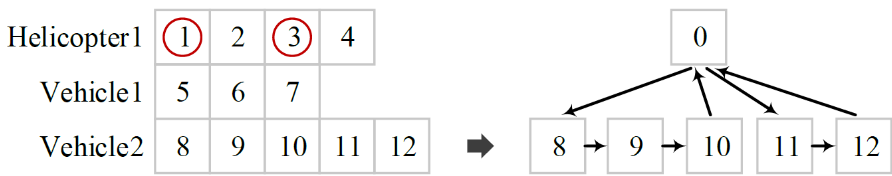

FIGURE 2. Chromosome structure

3.2. **Stochastic neighborhood search.** In view of reaching the solutions, the form of mutation operator in the traditional NSGA-II is single and it is easy to make the current solution show a wide range of fluctuation, which is not good for the local optimization of the solution, so we propose a stochastic neighborhood search algorithm based on the idea of variable neighborhood. On the one hand, select a neighborhood search operator randomly to reconstruct the chromosome to obtain a new chromosome; on the other hand, select randomly a local search operator to perform multiple exploratory reconstructions on the new chromosome, and determine whether to accept its reconstruction according to the acceptance criteria.

3.3. **Solution acceptance criteria.** For any two decision vectors $x_1, x_2 \in X$(*feasible solution set*) in the minimization problem [5]:

(1) x_1 is better than x_2 ($x_1 \succ x_2$), if and only if $f_i(x_1) < f_i(x_2)$, $\forall i = \{1, 2, \ldots, num_{obj}\}$;

(2) x_1 is weakly better than x_2 ($x_1 \succeq x_2$), if and only if $f_i(x_1) \leq f_i(x_2)$, $\forall i = \{1, 2, \ldots, num_{obj}\}$; and $f_i(x_1) < f_i(x_2)$, $\exists i = \{1, 2, \ldots, num_{obj}\}$.

Here, num_{obj} is the number of objective functions, $num_{obj} = 2$ in the text.

The child chromosomes x' are obtained by randomly neighborhood-searching of the parent chromosomes x. If x' is weakly better than x, that is $x_1 \succeq x_2$, add x' into the population and delete x; If x' does not dominate x, that is $x_1 \succ x_2$, delete x'; Otherwise, the probability function (17) is used to decide whether or not to join x' into the population.

$$p(x(k) \to x') = \begin{cases} 1, & f(x') < f(x(k)) \\ e^{-\frac{f(x')-f(x(k))}{T_i}}, & \text{others} \end{cases} \tag{15}$$

4. **Case Study.** On 12th May, 2008, one of the worst earthquakes in living memory, struck Sichuan Province, in which 68712 people were killed, 17921 people were missing and the direct economic losses reached 845.2 billion yuan. We take Mianyang, one of the worst-hit areas, as an example. According to the population distribution and the road damage after the earthquake in Mianyang, we establish 57 ordinary disaster areas and 10 isolated disaster areas, and regard the airports, lie on the south of Mianyang, as the relief supplies collection centers.

The parameters of NSGA-SNS-II algorithm are set as follows. The number of chromosomes $N = 50$, the maximum number of iterations $G_{\max} = 1000$, the maximum number of local neighborhood search $C_{\max} = 3$, the crossover probability $P_c = 0.8$, and the confidence level $\lambda = 0.8$. In order to verify the superiority of the algorithm, we use NSGA-II to solve the example and compare it with the NSGA-SNS-II algorithm that is proposed in this paper. The distribution of the initial solution and the Pareto optimal solutions of the two algorithms which are iterated to the maximum number are shown in Figure 3.

As can be seen from Figure 3, the solution distribution of the initial population has multiple levels, and there are a large number of dominated solutions. When the maximum number of iterations is reached, all solutions are non-dominated solutions and constitute the Pareto optimal frontier, which shows that the two algorithms can be effectively converged. However, the solution of NSGA-SNS-II dominates the solution of NSGA-II when the algorithm iterates to a certain number of times, so the optimization effect of NSGA-SNS-II is stronger.

The subjective preference value λ is an important factor that affects decision makers whether or not arrange rescue tools to the next disaster area. Therefore, this paper explores the influence of different confidence levels on the objective function value by means of sensitivity analysis numerical experiment. In Figure 4, with the increase of λ,

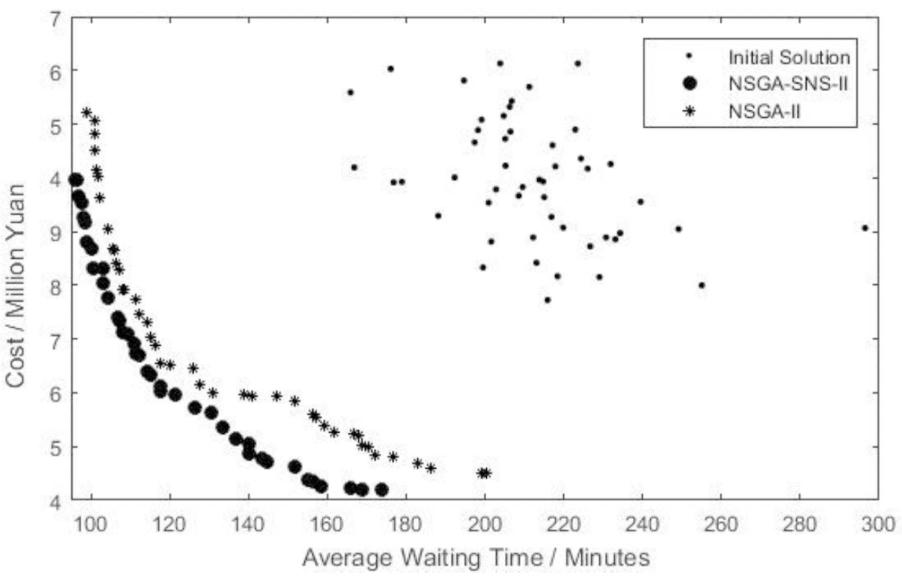

FIGURE 3. The optimization results comparison of NSGA-II and NSGA-SNS-II

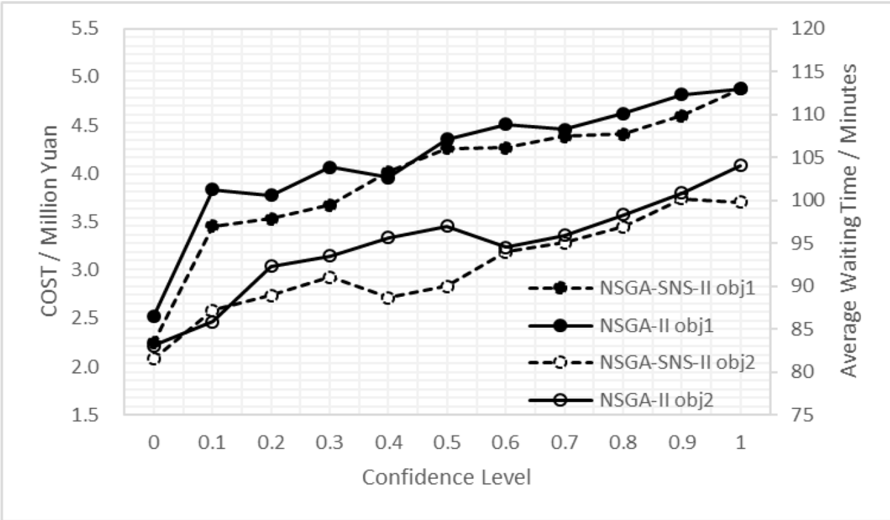

FIGURE 4. Sensitivity analysis

the constraints are more stringent, and the two objective function values tend to become larger, regardless of which algorithm. At the same time, in most cases, the objective value obtained by NSGA-SNS-II is smaller than NSGA-II when the algorithm iterates to a certain number of times, which shows that the NSGA-SNS-II algorithm can clipping get more effective solutions.

5. Conclusion.

Under the background of large-scale disaster, this paper studies the joint scheduling problem of two kinds of rescue tools (helicopter and vehicle), with the traffic constraints, the limited capacity and fuzzy demand, and takes the minimum waiting time of the disaster areas and the minimum economic cost of the emergency system as the objectives to generate the helicopter-vehicle joint scheduling plan in a short time, which can provide a support for decision makers. In the process of solving the model, the mutation operator of stochastic neighborhood search is constructed by using a variety of neighborhood operators, and an improved multi-objective algorithm is designed. The experimental results show that the advantage of NSGA-SNS-II algorithm is outstanding and can provide effective technical support for decision makers.

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