Research on the optimization of post-earthquake wounded rescue and transportation route considering the priority of disaster points

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Abstract: The earthquake is destructive and may cause large-scale casualties. Compared with the sharp increase in the number of wounded, rescue resources are obviously insufficient. Reasonable scheduling of disaster-relief vehicles is of great significance for rapid rescue work and shortening the rescue time. In this study, an emergency vehicle rescue scheduling with multiple rescue centers, multiple disaster points after the earthquake for the wounded is investigated. A multi-objective mixed integer linear programming model was used to simultaneously minimize the total rescue time and the rescue priority weight. In order to solve the problem efficiently, the ε-constraint algorithm and the two-stage algorithm are proposed. The ε-constraint algorithm transforms a multi-objective problem into a single-objective problem with ε-constraint, and then uses a single-objective optimization method to solve it. The two-stage algorithm divides the entire rescue area into multiple independent rescue areas, and converts multiple rescue centers into multiple single rescue center problems to improve solution efficiency. The effectiveness of the algorithm is verified by an arithmetic examples. Compared with the firefly algorithm, the two-stage heuristic algorithm is more efficient, and the solutions obtained by the ε-constraint method are better than the firefly algorithm, with higher quality and more numbers. Finally, the relationship between rescue time and priority rescue weight, and the influence of the number of rescue vehicles on scheduling decisions are discussed.

Keywords: Earthquake disaster; Rescue route； Earthquake rescue; Multi-objective optimization; ε-constraint algorithm; Two-phase solution.

1. INTRODUCTION

Earthquake is one of the most serious natural disasters causing casualties and urban destruction, which is characterized by suddenness and wide spread. The victims of the earthquake disaster are widely distributed, the injuries of the wounded may gradually deteriorate, and the transportation network in the earthquake area has been damaged to a certain extent. Therefore, in the face of the timeliness of the wounded rescue and the large demand for medical resources, it is particularly important to organize emergency rescue activities quickly, shorten rescue time as much as possible and improve rescue efficiency. It is also necessary to reasonably allocate rescue resources according to the disaster situation in each disaster area and to promptly arrange rescue vehicles to transfer the wounded to rescue centers.

At present, the research on the optimization of earthquake rescue problems mainly focuses on the optimization of emergency material facilities site selection and optimization of emergency material distribution paths, with emphasis on improving material distribution efficiency and economic benefits. (Vahdani et al., 2018) proposed a two-stage multi-commodity, multi-objective mixed integer site-routing-inventory model for effective distribution of relief supplies, and designed two heuristic algorithms, nondominated sorting genetic algorithm II (NSGA-II) and multi-objective particle swarm optimization (MOPSO), to solve the problem. (Yi et al., 2019) studied the emergency rescue vehicle routing problem (EmVRP), constructed an optimization model for emergency rescue supplies in sudden disasters with the goal of satisfying the demand at the affected point in the shortest total operating time, and proposed an improved imperial butterfly algorithm for solving the problem. (Mohsen et al., 2018) argued that the occurrence of disasters has a huge impact on the transport networks of developing countries in particular. They proposed to minimize the network length, total travel time, and total number of paths through each link as performance indicators for evaluating network vulnerability to solve the emergency transport optimal routing problem and apply branch delimitation to solve it. The above study considered the impact of the post-earthquake transportation system on vehicle travel time and material requirements. However, post-earthquake rescue should focus on the efficiency of treatment and transfer of the injured, because it is a struggle against time, and if the "golden 72 hours" of rescue is exceeded, the possibility of rescue of survivors will be significantly reduced (Chiu et al., 2020). Although emergency material distribution and wounded rescue are both emergency rescue, they have big differences, mainly in aspects such as the number of casualties, the wide range of disaster areas, long rescue time and great difficulty, which makes the rescue of casualties under large-scale emergencies extremely difficult.

On the other hand, research on the scheduling of wounded rescue vehicles under emergencies has focused on constructing reasonable emergency rescue vehicle routing planning models to more closely match post-disaster rescue scenarios. (Zhu et al., 2017) expressed the difference in disasters in terms of "the time the casualty can persist in transit", and studied the inter-regional emergency rescue routing problem with time window constraint and disaster differentiation, taking the minimization of rescue vehicle travel time as the optimization goal and solving it by using ant colony algorithm (ACO). Sun et al., (2020) analyzed the impact of dynamic changes of ambulance vehicles and medical resources on wounded evacuation plan after the earthquake, constructed a multi-objective optimization model with maximum number of injured survivors and minimum psychological cost of wounded rescue, and applied the ε-constraint algorithm to solve it. Nader et al., 2017) studied the post-disaster humanitarian relief problem by considering commodity delivery, casualty evacuation, and dispatching relief workers to the affected area simultaneously in the same model for the first time, aiming to minimize the number of unsatisfied goods, the number of wounded who had not been evacuated, and the staff who had not been transferred.

It can be seen that most of the existing studies focused on the location of facilities and vehicle path planning for emergency supplies under emergencies, while there are fewer studies on the routing selection of casualty rescue vehicles. Most of the existing studies took rescue task completion time, rescue cost or number of injured survivors as the optimization target, but they did not analyze and evaluate the trauma situation and rescue priority of the wounded, which cannot well reflect the requirements of seriously injured people on the time efficiency of emergency treatment. More recently, Wang et al., 2017) focused on the injury grade of the wounded in their study, and dispatched the ambulance vehicles according to the different rescue priorities of the wounded. Based on the post-earthquake rescue area division, Wang et al. 2018) constructed a nonlinear planning model for vehicle scheduling of a single rescue center with the shortest total rescue time and maximized rescue weights at the disaster site, and proposed a firefly algorithm for solving the model.

For a new category of post-earthquake multi-disaster site wounded classified treatment and emergency vehicle dispatch problems, this paper comprehensively considers the rescue vehicle's arrival time, multiple types of wounded and distance factors, and constructs a bi-objective mixed-integer linear programming model with the shortest rescue time and the minimization of priority rescue weights. Based on the scenario that multiple rescue centers respond to rescue requests from multiple disaster points after the earthquake, ε-constraint algorithm is used to optimize the path of the wounded rescue vehicles. In order to obtain the solution quickly, a two-stage solution method is proposed: the first stage is to divide the rescue area, and propose a division standard that considers the number of injured and distance factors at the same time; in the second stage, a multi-objective mixed integer linear programming model for a single rescue center is constructed based on the division of the area, solved using an iterative exact ε-constrained algorithm, and then a fuzzy logic approach is applied to help decision makers formulate a rescue plan. Compared with the literature (Wang et al., 2018), the main contribution of this paper is: 1) This paper proposes a multi-objective mixed integer linear programming model for classified treatment of wounded and emergency vehicle scheduling in disaster-prone areas after earthquakes is proposed; 2) Two solution methods are proposed for the exact and approximate solution of the model, and the results of the benchmark case tests show the accuracy and effectiveness of the model and algorithm; 3) The experimental results show that there is a mutual constraint between the rescue time and the priority rescue weight value. If too many resources are prioritized to the disaster site with severe disaster, it will cause other disaster sites to wait too long for rescue and increase the total rescue time, and vice versa.

2. PROBLEM DESCRIPTION AND MODELING

2.1 Problem description

There are n disaster sites, w rescue centers, and k vehicles per rescue center. An example of post-earthquake wounded treatment and transportation is shown in Figure 1. Based on the data provided by the earthquake emergency command center, the location of each disaster site and the number of casualties are predicted, and each rescue vehicle departs from its own rescue center and returns to its own rescue center after completing the rescue mission. The maximum number of vehicle loads is unique and known, and the rescue vehicle needs to arrive at the disaster site to treat and transfer the wounded before the latest time window. Each disaster site will be rescued once. For modeling purposes, the following assumptions are made: (1) The number of wounded treated by the rescue center does not exceed its maximum capacity; (2) The vehicle types are consistent; (3) The travel time of the rescue vehicle is much greater than the rescue time at each disaster site, so the rescue time of the rescue vehicle at the disaster site can be neglected; (4) Only consider the current transportation network in which vehicles can reach the disaster area and ignore the need for helicopters or other special transportation.

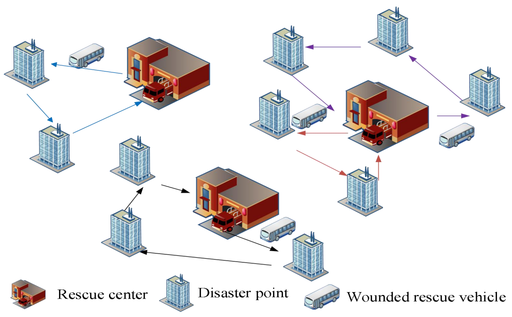

Figure 1. Example of post-earthquake wounded treatment and transportation.

2.2 Symbol description

$A = \{(i,j): i \neq j \in N\}$: the arc set of i,j;
$V_d = \{1,2,3,\cdots,w\}$: the set of real rescue centers;
$V_c = \{w+1, w+2, w+3, \cdots, w+n\}$: the set of all disaster sites;
$V_f = \{n+w+1, n+w+2, n+w+3, \cdots, n+2w\}$: a virtual rescue center corresponding to V_d called a virtual set of rescue centers;
$N = \{1,2,3,\cdots,n+2w\}$; $N = V_c \cup V_d \cup V_f$; the set of all nodes;
K_i: the vehicles belonging to rescue center i, $i \in V_d$;
$K = \{K_1 \cup K_2 \cup K_3 \cup \cdots \cup K_i\}$: the set of rescue vehicles;
q_i: the number of wounded at disaster site i;
t_{ij}: the travel time from node i to node j;
F_i: the urgency of rescue needs at disaster site i;
Q_k : the maximum number of people loaded by rescue vehicle k;
D_j : the latest time for each rescue vehicle to reach the disaster site j;
M: a fairly large positive number;

Decision variables:
X_{ijk}: if the rescue vehicle k goes from node i to node j, it takes the value of 1, otherwise it is 0;
T_{ik}: the time of rescue vehicle k arriving at disaster site i ;

2.3 Multi-objective mixed-integer linear programming model for multi-rescue center response

Objective function:

$$min\, f_1 = \sum_{k\in K} \sum_{i\in N} \sum_{j\in N} t_{ij} X_{ijk} \quad (1)$$

$$min\, f_2 = \sum_{k\in K} \sum_{i\in V_c} \frac{T_{ik}}{F_i} \quad (2)$$

Constraint condition:

$$\sum_{i\in N} \sum_{k\in K} X_{ijk} = 1, \forall j \in V_c \quad (3)$$

$$\sum_{j\in N} \sum_{k\in K} X_{ijk} = 1, \forall i \in V_c \quad (4)$$

$$\sum_{i\in N} X_{ihk} - \sum_{j\in N} X_{hjk} = 0, \forall h \in V_c, \forall k \in K \quad (5)$$

$$\sum_{i\in V_d \cup V_c} \sum_{j\in V_c} q_i X_{ijk} \leq Q_k, \forall k \in K \quad (6)$$

$$\sum_{j\in N} X_{ijk} = 1, \forall k \in K_i, \forall i \in V_d \quad (7)$$

$$\sum_{i\in N} X_{ijk} = 1, \forall k \in K_j, \forall j \in V_f \quad (8)$$

$$\sum_{i\in N} X_{ijk} = 1, \forall k \notin K_j, \forall j \in V_d \quad (9)$$

$$\sum_{j\in N} X_{ijk} = 1, \forall k \notin K_i, \forall i \in V_d \quad (10)$$

$$T_{ik} + t_{ij} - M(1 - X_{ijk}) \leq T_{jk}, \forall k \in K, \forall i,j \in N \quad (11)$$

$$T_{jk} \leq D_j, \forall j \in V_c, \forall k \in K \quad (12)$$

$$T_{ik} = 0, \forall k \in K, \forall i \in V_d \quad (13)$$

$$\sum_{i\in N} X_{iik} = 0, \forall k \in K \quad (14)$$

The objective function (1) represents the minimization of the total rescue time; The objective function (2) means to minimize the priority value of rescue weight. Constraints (3) and (4) indicate that each disaster site can only receive one rescue service. Constraint (5) indicates the flow balance constraint. Constraint (6) indicates that the number of wounded transferred by the rescue center cannot exceed its maximum load. Constraints (7) and (8) indicate that each rescue vehicle can leave and return to the rescue center to which it belongs at most once. Constraints (9) and (10) indicate that each rescue vehicle is guaranteed to depart from and return to the rescue center to which it belongs. Constraints (11) and (12) stipulate that each rescue vehicle must arrive at the disaster site by the latest arrival time. Constraint (13) specifies that the starting time of each rescue vehicle from the rescue center is 0. Constraint (14) stipulates that each rescue vehicle cannot travel to and from the same node.

2.4 Wounded classification and number of wounded forecast

2.4.1 Wounded classification

Significantly more people were seriously injured than killed by the earthquake (Liu et al., 2015). The presence of a large number of injured people in a short period of time undoubtedly challenged the rescue capacity and speed of local medical institutions. If more medical resources are spent on the seriously injured according to the usual method of treatment, there will often be unsatisfactory treatment of the seriously injured or the lightly injured will be forced to amputate their limbs due to untimely treatment, and more serious cases will result in death. Therefore, we should first examine and classify the wounded in order to rationalize the use of medical resources and reduce the disability and mortality rate of the wounded.

Referring to the World Health Organization (WHO) classification method for injury detection, four colors are used to indicate the degree of injury respectively. Green represents the lightly wounded, which require only simple treatment and do not require rescue vehicle transfer. Yellow indicates moderate injuries, treatment can be delayed, but should be transferred to the nearest hospital for medical treatment within the specified time. Red is a serious injury, this type of wounded should be treated immediately and urgently transferred to a hospital for treatment, such as symptoms, excessive blood loss and severe shock. Black is a very serious wounded, which do not need to be transferred to a hospital and have a very low chance of survival.

2.4.2 Number of wounded forecast

There are many factors that can cause casualties when an earthquake occurs, such as the magnitude of the earthquake, the time of the earthquake, the structure of the building, the seismic performance of the building, etc. (Liu et al., 2015). This paper estimates the post-earthquake death toll by the formula:

$$D_i = \sum_{j=1}^{4} s_j c_j d_j i_j \rho_j \tag{15}$$

D_i represents the predicted number of deaths at disaster site i. s_j represents the area that may be destroyed by building category j. c_j represents the collapse rate of building category j under a certain earthquake magnitude. d_j represents the death rate of people within the collapsed area of building category j. i_j represents the occupancy rate of people in different time periods in building category j. ρ_j represents the indoor occupant density of building j.

Considering that the moderate and severe wounded need to be promptly transferred to hospitals for treatment, while the other two types of wounded do not, so this paper takes these two types of wounded as rescue objects, and the prediction formula for the number of moderate and severe wounded is:

$$D_{im} = u_m D_i \tag{16}$$

Where D_{im} represents the number of wounded of category m at disaster site i. u_m represents the ratio coefficient of the number of wounded in category m to the number of predicted deaths.

2.5 Calculation of the urgency of rescue needs

In the early stages of an earthquake, there may be a large number of injured people in certain areas, but relief supplies are relatively short, so it is necessary to assess the situation to determine which disaster sites should be given priority. This paper mainly measures the urgency of rescue needs in terms of distance and the number of wounded.

2.5.1 Calculation of relative weights of wounded factors

The type of wounded affects the priority order of rescue, so weights of $\beta = 1, \alpha = 0.5$ were respectively assigned to moderate and severe wounded. The wounded factor rescue weights for each disaster site are:

$$W_i = D_{i1}\alpha + D_{i1}\beta \tag{17}$$

D_{i1} and D_{i2} represent the estimated number of severely wounded and lightly wounded, respectively.

The wounded factor rescue weights were then dimensionless, and the relative weights of the wounded factors were:

$$DW_i = \frac{D_{i1}\alpha + D_{i1}\beta}{\sum_{i=1}^{I} D_{i1}\alpha + D_{i1}\beta} \tag{18}$$

In addition, I denotes the set of disaster sites.

2.5.2 Calculation of relative weights of distance factors

The earthquake will destroy the road connectivity, so the original data cannot be used to calculate the distance between the disaster site and the rescue center. If recalculating the length of each path is time-consuming and labor-intensive, it does not meet the post-earthquake emergency relief requirements. Therefore, the Euclidean distance d_{ij}' between two disaster sites is used to calculate the relative weight LW_i of the distance factor, which is calculated as follows:

$$LW_i = \frac{d_{ij}'}{\sum_{i=1}^{I} d_{ij}'} \tag{19}$$

Combining these two factors, the urgency of the rescue need at disaster site i is:

$$F_i = w_1 DW_i + w_2 LW_i \tag{20}$$

In addition, considering that the primary task of post-earthquake rescue is to treat the wounded, the wounded factor weight w_1 is given as 0.6 and the distance factor weight w_2 is given as 0.4, respectively (Wang et al., 2018).

2.6 Predicted travel time of rescue vehicles

Due to the devastating nature of the earthquake disaster, houses beside the road may collapse and vehicles cannot pass normally, making the travel time of rescue vehicles difficult to predict. This paper mainly considers the impact of five aspects on the speed of rescue vehicles: the type of road after the earthquake, the time period when the earthquake occurred, road occupation by collapsed buildings, the length of the road section, the number of forks, and their correction factors for the speed of the vehicle are r_0,t_0,c_0,l_0, and f_0. The formula for the travel time of rescue vehicles between the two disaster sites is:

$$t_{ij} = \frac{d_{ij}}{v_{ij} r_0 t_0 c_0 l_0 f_0} \tag{21}$$

Where d_{ij} is the actual distance from disaster site i to disaster site j, and v_{ij} is the travel speed corresponding to different road types under daily conditions.

3. SOLVING ALGORITHM

In order to solve the problem efficiently, two types of solution methods are proposed: use the ε-constraint method to find the exact Pareto-front of the problem; design a two-stage heuristic algorithm that can solve the problem in a short time.

3.1 Design of ε-constraint Method

This algorithm is one of the most commonly used methods for solving multi-objective optimization problems, and it can solve multi-objective optimization problems exactly compared to other heuristic algorithms. The principle is to transform the multi-objective problem into a single-objective problem with ε-constraint, and then apply the single-objective optimization method to solve it. The function values of all objectives can be calculated in each iteration, since they have the same solution space (He et al., 2020). After one iteration, if the ε value does not satisfy the algorithm end condition, the ε value is updated and the above process is repeated until the algorithm end condition is satisfied, and finally the optimal Pareto-front point is obtained.

In order to better explain that the ε-constraint method can accurately solve the bi-objective model, first explain the concept of Pareto dominance (Zheng et al., 2018). For the simultaneous optimization of the minimization bi-objective, Pareto dominance relation can be expressed as: if there exists a feasible solution X_1 better than another feasible solution X_2 (X_1 and X_2 are vectors), thus there must exist $f_1(X_1) \le f_1(X_2)$ as well as $f_2(X_1) \le f_2(X_2)$, and it is stipulated that at least one inequality sign must be less-than sign. With the concept of Pareto dominance, all non-dominated points obtained in the feasible solution space of the objective function constitute the Pareto-front, and there is no dominance relationship between any two points on the Pareto-front.

According to the characteristics of earthquake disaster rescue work with time urgency, the shortest rescue time is taken as the main objective function, and the priority rescue weight value is taken as the ε-constraint. Based on the mixed integer linear programming model established above, the model P_1 transformed by the ε-constraint method is as follows:

$\min f_1$

$s.t.$

$f_2 \le \varepsilon_i$

(3) ~ (14)

Based on the bi-objective minimization optimization problem established above, the ε-constraint method is calculated as follows:

Step 1: Calculate the ideal point $f^I = (f_1^I, f_2^I)$ and the lowest point $f^N = (f_1^N, f_2^N)$, where $f_1^I = \min f_1$, $f_2^I = \min f_2$, $f_1^N = \min\{f_1, f_2\}$, $f_2^N = \min\{f_2, f_1^I\}$, set a non-dominated solution $\Omega = \emptyset$;

Step 2: Update $\Omega = \Omega \cup \{(f_1^I, f_2^N), (f_1^N, f_2^I)\}$, set $\varepsilon_i \in [f_1^I, f_2^N]$, f_2^I, f_2^N, set step length $\Delta = 10$;

Step 3: Set $i = 2$, $\varepsilon_i = f_2^{i-1} - \Delta$ to build the model P_1;

Step 4: Determine if $\varepsilon_i \ge f_2^I$ is satisfied;

Step 5: If $\varepsilon_i \ge f_2^I$, then accurately solve the model P_1, Calculate the value of the objective function (f_1^i, f_2^i) for each iteration, update Ω, and make $i = i + 1$, $\varepsilon_i = f_2^{i-1} - \Delta$. If step 4 is not satisfied, stop the iteration;

Step 6: Remove the dominating solution from the set Ω to obtain the Pareto-front point.

3.2 Design of two-stage heuristic algorithm

The ε-constraint method can solve small-scale problems accurately, but its solution takes a lot of time when solving large-scale problems. To improve the efficiency of the solution, the sub-problem of the problem, i.e., the rescue vehicle scheduling problem with multiple single rescue centers, is studied and a two-stage solution method is proposed. The first stage is to divide the rescue area, taking into account the distance from the disaster site to the rescue center and the number of wounded, and assign the disaster site to the corresponding rescue center. The second stage is based on dividing the disaster area, and then applying the iterative exact ε-constraint method to solve the established single rescue center multi-objective mixed integer linear programming model to obtain the Pareto solution. The fuzzy set theory approach is then used to help decision makers determine a compromise solution from the Pareto solution set and develop a reasonable emergency rescue plan.

3.2.1 Rescue area division

In this paper, we use aggregation optimization algorithm to divide the whole rescue area into multiple independent rescue areas and transform multiple rescue centers into multiple single rescue center problems. The key to the aggregation optimization algorithm is to compare the distance value of any disaster site from two nearby rescue centers, which is expressed as Euclidean distance. The edge coefficient η represents the ratio of the distance values of any disaster site to the two rescue centers in close proximity. When the distance between a disaster site and a rescue center is significantly shorter than the distance from the site to other rescue centers, i.e., the edge coefficient is small, it will be included in the rescue area of the rescue center. Otherwise, it is included in the set of edge points. The calculation steps are as follows:

Step 1: calculate the Euclidean distance between two points

$\{d_{ij} | i = 1,2,3, \cdots, n; j = n+1, n+2, n+3, \cdots, n+m\}$,

where i represents the disaster site, j represents the rescue center;

Step 2: calculate the edge coefficient value of the disaster point: $f_{ij}=\frac{d_{ij_{n+1}}}{d_{ij_{n+2}}}$, $d_{ij_{n+1}}$ denotes the distance value of the disaster point from the nearest rescue center, $d_{ij_{n+2}}$ denotes the distance value of the disaster point from the next closest rescue center;

Step 3: compare the set edge value η with f_{ij}. If $f_{ij}<\eta$, then disaster point i is rescued by rescue center j_{n+1}. If $f_{ij}>\eta$, then disaster point i is classified to the set of edge points, which belong to the edge points of rescue centers j_{n+1} and j_{n+2};

Step 4: according to the distribution of disaster points, the second distribution of disaster points that are classified into the edge collection combined with the number of wounded is carried out until the disaster points are completely divided.

3.2.2 Optimization method of rescue vehicle dispatching for single rescue center

(1) Parameter description

$S=\{0,1,2,3,\cdots,n+1\}$: The set of all nodes; $1,2,3,\cdots,n$ denotes the disaster site, 0 and $n+1$ denote the real and virtual rescue centers, respectively.

$C=\{1,2,3,\cdots,n\}$: The set of all disaster sites.

(2) Rescue vehicle dispatching model of single rescue center

$$min\, f_3=\sum_{k\in K}\sum_{i\in S}\sum_{j\in S}t_{ij}X_{ijk} \quad (22)$$

$$min\, f_4=\sum_{k\in K}\sum_{i\in C}\frac{T_{ik}}{F_i} \quad (23)$$

$s.t.$

$$\sum_{k\in K}\sum_{j\in S}X_{ijk}=1,\forall i\in C \quad (24)$$

$$\sum_{i\in S\setminus n+1}\sum_{j\in C}q_jX_{ijk}\le Q_k,\forall k\in K \quad (25)$$

$$\sum_{j\in S}X_{0jk}=1,\forall k\in K \quad (26)$$

$$\sum_{i\in S}X_{i,n+1,k}=1,\forall k\in K \quad (27)$$

$$\sum_{i\in S}X_{ihk}-\sum_{j\in S}X_{hjk}=0,\forall k\in K,\forall h\in C \quad (28)$$

$$T_{ik}+t_{ij}-M\left(1-X_{ijk}\right)\le T_{jk},\forall i,j\in S,\forall k\in K \quad (29)$$

$$T_{jk}\le D_j,\forall j\in S,\forall k\in K \quad (30)$$

$$T_{0k}=0,\forall i\in C,\forall k\in K \quad (31)$$

$$\sum_{i\in S}X_{kii}=0,\forall k\in K \quad (32)$$

The objective function (22) represents the minimization of the total rescue time; the objective function (23) represents the minimization of the priority rescue weight value; constraint (24) stipulates that each disaster site can receive rescue service and only one rescue vehicle can provide rescue service; The constraint (25) stipulates that the number of wounded persons transferred by each rescue vehicle shall not exceed the maximum carrying capacity of the vehicle; constraints (26) and (27) stipulate that each rescue vehicle must return to the rescue center after starting from the rescue center; constraint (28) means the flow balance constraints, etc. Constraints (29) and (30) stipulate that each rescue vehicle must arrive at the disaster site before the latest time; constraint (31) stipulates that the starting time of the rescue vehicle from the rescue center is 0; constraint (32) means that each rescue vehicle can not travel to and from the same node.

(3) an algorithm based on ε-constraint iteration and fuzzy logic

In the same way as the multi-rescue center response and rescue solution, the exact iterative ε-constraint method is used to solve the single rescue center's rescue vehicle scheduling problem, the model P_2 transformed by the ε-constraint method is as follows:

$$\min \mathrm{f}_3$$

$$\mathrm{s.t.}$$

$$\mathrm{f}_4\le\varepsilon$$

(24) - (32)

The calculation method of fuzzy set theory can help the decision maker to choose a compromise solution from the non-dominated solution set according to the decision preference (Wang et al., 2020), the calculation steps of fuzzy set theory are as follows:

Step 1: using formula (33) to calculate the optimal index $\delta_i\left(f_i^k\right)$ of each solution corresponding to each objective function in the non-dominated solution set;

$$\delta_i\left(f_i^k\right)=\begin{cases}1, & f_i^k\le f_i^I\\ \frac{f_i^N-f_i^k}{f_i^N-f_i^I}, & f_i^I<f_i^k<f_i^N\\ 0, & f_i^k\ge f_i^N\end{cases} \quad (33)$$

Among them, i is the i -th objective function, k is the $k-$ th non-dominated solution solution, and the formula (33) is used to solve the optimization problem.

Step 2: according to (34) calculating the comprehensive optimization index δ^k of the solutions in the non-dominated solution set;

$$max\{\delta^k\} = max\left\{\frac{\sum_{i=0}^{m}\delta_i\left(f_i^k\right)}{\sum_{i=1}^{m}\sum_{k=1}^{K}\delta_i\left(f_i^k\right)}\right\} \tag{34}$$

Among them, m represents the number of objective functions, and the non-dominated solution corresponding to the maximum comprehensive optimization index is the compromise solution of the multi-objective optimization problem. If the decision maker has a different preference for each objective function, skip this step and move to step 3.

Step 3: calculate the preferred index δ^k according to Formula (35).

$$\delta^k = max\left\{\frac{\sum_{i=0}^{m}w_i\delta_i\left(f_i^k\right)}{\sum_{i=1}^{m}w_i}\right\} \tag{35}$$

Where w_i is the weight value of the i-th objective function.

4. CASE STUDIES

In this part, we analyze the characteristics and algorithm validity of the wounded transfer and emergency vehicle scheduling problem with multi-rescue centers, multi-disaster sites and multi-rescue vehicles. The contents include: comparative analysis of firefly algorithm, ε -constraint method and two-stage heuristic solution; study of problem attributes, including the relationship between rescue time and priority, this paper explores the influence of the number of rescue vehicles on the dispatch and route selection of rescue vehicles, and uses the fuzzy logic theory to help the decision-makers to choose rescue plans according to their preference. All of the experiments were programmed with CPLEX, Computer configuration Intel Core i5-4200H 2.80GHz, 8 GB RAM, and executed on Windows 10.

4.1 Experimental data

The experimental data in this paper are from reference (Wang et al., 2018), including the latest arrival time, the weight value of rescue demand and the number of wounded. For detailed data, see Table 1. In this example, it is assumed that an earthquake of magnitude 5 will occur at 3:00 pm in a city. There are 33 nodes in the earthquake area. The type of rescue vehicle is the same as the number of approved loading personnel, and each rescue vehicle can transfer up to 30 people. The correction coefficient c_0 of building collapse along the street to vehicle speed is 0.65, and the influence coefficient t_0 of earthquake time period to road network traffic is 1. In this paper, an aggregation optimization algorithm is proposed to divide the rescue area into three areas marked by A1, A2 and A3, where three nodes (number: 12, 22, 32) are used as the rescue center, the rescue area A1 includes nodes 8, 9, 10, 11, 12, 13, 14, 15, 18, 19, 20, 23; The rescue area A2 includes nodes 3, 4, 5, 6, 7, 16, 17, 21, 22, 26, 27; the rescue area A3 includes nodes 1, 2, 24 ,25 ,28 ,29 ,30 ,31 ,32, 33.

Table 1. Relevant information for each disaster site

Disaster site number	Number of wounded	Latest arrival time (min.)	Priority rescue weight
1	8	3	0.0309
2	8	13	0.0384
3	7	5	0.0314
4	5	3	0.0207
5	17	11	0.0590
6	7	7	0.0288
7	3	20	0.0266
8	8	5	0.0278
9	4	12	0.0205
10	7	9	0.0190
11	8	4	0.0329
13	3	5	0.0241
14	9	20	0.0346
15	8	8	0.0344

16	9	10	0.0306
17	11	12	0.0388
18	3	9	0.0313
19	7	14	0.0307
20	12	13	0.0443
21	8	6	0.0293
23	4	9	0.0364
24	4	20	0.0294
25	9	20	0.0390
26	8	10	0.0325
27	8	8	0.0308
28	4	13	0.0319
29	11	23	0.0454
30	8	11	0.0364
31	7	13	0.0290
33	15	10	0.0541

4.2 Comparative analysis of three algorithms

In order to verify the validity and correctness of the model and algorithm presented in this paper, the-constraint method and the two-stage heuristic are compared with the firefly algorithm presented in (Wang et al., 2018). The results are shown in Table 2.

Table 2. Comparison of the results of the firefly algorithm method and the two-stage heuristic method

Comparison item	Firefly algorithm	Precision ε-constraint method	Two-stage heuristic
(f_1, f_2)	(206.4, 8747.74)	(199.7,7946.2), (201.4, 7432.51)	(206.4, 8747.74)
CPU/s	-	216559	225.39

- indicates that reference (Wang et al., 2018) does not give the running time of the firefly algorithm

The second row in Table 2 shows the minimum rescue time and the minimum priority rescue weight obtained by three different methods, and the third row shows the solution time. The results show: (1) compared with the firefly algorithm, the solutions calculated by the ε-constraint method are all exact solutions, and the solutions are of higher quality and more numerous, and the 2 objective function values corresponding to the 2 solutions are better than those of the firefly algorithm, saving rescue time by 2.92% on average and reducing the rescue demand weight value by 12.1%, indicating that the ε-constraint method has significant advantages for solving the multi the overall rescue problem of the rescue center has significant advantages. (2) The solution results of the two-stage heuristic algorithm are consistent with the firefly algorithm, indicating the effectiveness of the two-stage heuristic algorithm for solving multiple single rescue center partitioned rescue problems. Although it is not possible to compare the solution time of the two-stage heuristic algorithm with that of the firefly algorithm, the two-stage method proposed in this paper can quickly obtain a rescue solution in a relatively short time (less than 4 min running time).

Compared with the firefly algorithm, the-constraint method and the two-stage heuristic method can effectively solve the problems of multi-rescue centers and multi-disaster locations in casualty treatment and emergency vehicle scheduling. The ε-constraint method can not only ensure the solution to be exact, but also provide multiple rescue plans for emergency management decision-makers. The two-stage heuristic can get a quick solution in a short time, which shows that the two-stage heuristic has the advantage of quickly solving the problem of regional rescue, at the same time, it shows the importance of the emergency rescue plan under the tight time of earthquake rescue.

4.3 Analysis of the relationship between minimum rescue time and priority rescue

In order to explain the relationship between rescue time and priority rescue weight in detail, an example is designed in this section for analysis, as shown in Figure 2. Assuming that there is only one rescue center, one rescue vehicle and three disaster sites in the example, the latest arrival time of the three disaster sites is 15 minutes, 23 minutes and 25 minutes respectively, and the number of wounded is 26, 2 and 1 respectively, the number on the arc represents the travel time from the node i to the node j, and the results are shown in Table 3.

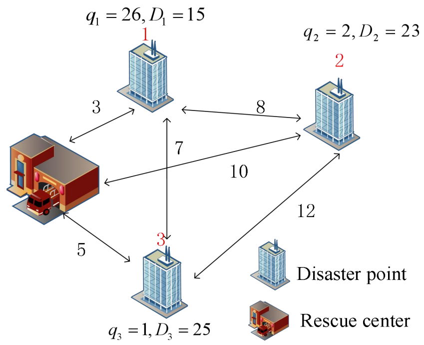

Figure 2. Schematic diagram of the distribution distance between the rescue center and the disaster point

Table 3. Calculation result of an example

Rescue route	Rescue time (min.)	Priority rescue weight value
1→2→3	28	271.65
1→3→2	32	172.75
3→1→2	30	140.84
3→2→1	28	150.33

Table 3 shows: 1) if only the shortest rescue time is taken into account and the priority weight is ignored, the rescue route is 1→2→3 or 3→2→1; if only the priority weight is minimized, the rescue route is 2→3→1. 2) In the actual rescue process, there is a situation where the number of disaster points is greater than the number of rescue vehicles, that is, the rescue resources are limited. The rescue vehicles will go to the disaster points with more serious disaster situation according to the priority rescue weight value, but it will cause the waiting time of the disaster points that need to be rescued later to be too long.

Taking the rescue route 1→2→3 as an example, its priority rescue weight value is $4.93 + 45.45 + 176.9 = 271.65$. Observing the calculation formula, we can see that the priority rescue weight value of disaster point 1 is the smallest, the priority rescue point 1 is followed by disaster point 2 and disaster point 3, however, the waiting time at disaster point 3 will be lengthened a lot, which will increase the total rescue time. Therefore, more rescue vehicles will be needed to solve the above problems. The results show that there is no one solution and the two objective functions are optimized at the same time, and the shortest rescue time and priority rescue restrict each other, this counterbalance can be alleviated by increasing the number of rescue vehicles.

4.4 The influence of the number of rescue vehicles on the dispatching decision

In order to analyze the impact of the number of rescue vehicles on the rescue vehicle scheduling plan, this section tests the impact of different numbers of rescue vehicles on the vehicle scheduling of single rescue center partition rescue and multi-rescue center overall rescue. The results are shown in Figure 3 and Table 4.

Table 4. Results of two-stage heuristic calculation for 4,6 and 8 vehicles in the rescue center

Rescue area	4	6	8
A_1	(64.5, 3205.94)	(64.5, 3205.94)	(64.5, 3205.94)

	(67, 2525.47) (78.4, 2351.96)	(67, 2525.47) (76.6, 2034.1) (81, 1815.9)	(67, 2525.47) (76.6, 2034.1) (81, 1815.9)
A_2	(60.9, 2722.07) (62.1, 1538.03)	(60.9, 2722.07) (62.1, 1538.03) (74.3, 1522.77) (74.7, 1453.27)	(60.9, 2722.07) (62.1, 1538.03) (74.3, 1522.77) (74.7, 1453.27)
A_3	(81, 2819.73) (82.7, 1878.59)	(81, 2819.73) (82.7, 1878.59) (103.1, 1788.28)	(81, 2819.73) (82.7, 1878.59) (103.1, 1788.28)
CPU/s	1036.75	1482.89	1869.3

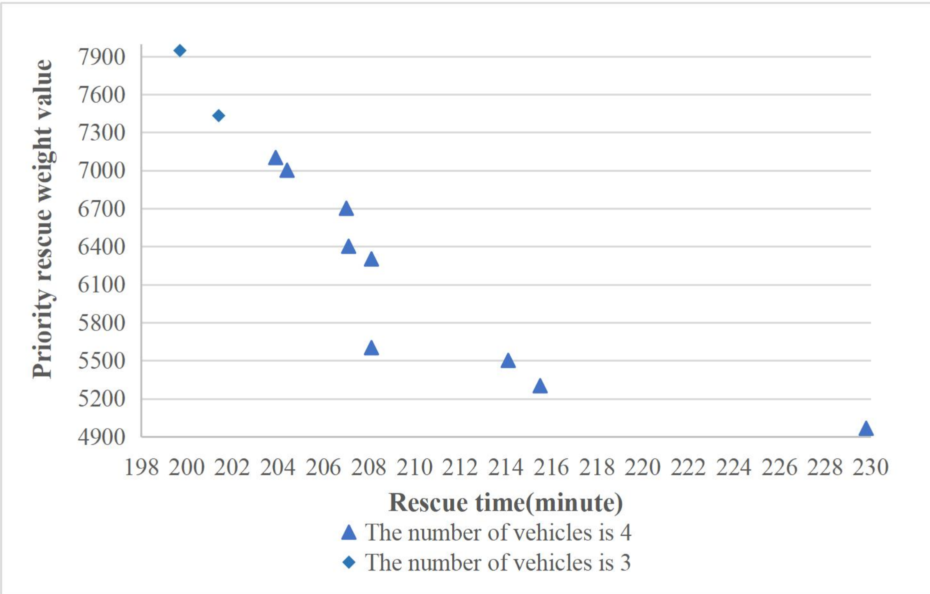

Figure 3. The solution result of ε-constraint method when the number of rescue vehicles is 4

As can be seen from Table 4, the number of Pareto solutions increases with the increase of rescue vehicles. This is due to the increase in the number of rescue vehicles, so that rescue routes are also increasing, and will affect the casualty rescue vehicle scheduling decisions. In addition, the number of Pareto solutions does not increase when the number of rescue vehicles increases from 6 to 8. This is because 6 rescue vehicles are sufficient to meet the rescue needs of this area, even if the additional vehicles, the solution will not change. When the number of rescue vehicles reaches a certain number, the number of Pareto solutions does not change, and 6 emergency rescue vehicles are needed in each rescue center to meet the demand of rescue activities.

As can be seen from Figure 3, when the number of rescue vehicles in each rescue center is increased from 3 to 4, the rescue time is longer than that of 3 rescue vehicles, the priority rescue weight is smaller than that of 3 rescue vehicles, and the number of Pareto solutions is obviously increased. This is because the number of relief programs is increasing with the increase in relief resources, and relief vehicles give priority to disaster-stricken areas, thus reducing the priority weight, but increasing the number of vehicles will make the overall relief time longer. This shows that the number of rescue vehicles has an important impact on the dispatching decision-making of casualty rescue vehicles. Therefore, emergency management decision makers need to deploy a reasonable number of rescue vehicles according to the actual situation.

As can be seen from Table 4 and Figure 3, with the increase of rescue vehicles, both the two-phase solution and the constraint method show that the rescue time increases with the decrease of the priority rescue weight, it shows that it is difficult to minimize the rescue time and the priority rescue weight at the same time. It needs the decision-maker to choose a scientific rescue plan according to the preference of these two goals.

4.5 Choice preference solutions

The method of fuzzy logic theory can help decision-makers to weigh the two-objective optimization problem according to their own decision preference. Taking 6 casualty rescue vehicles as an example, two objective functions with different weight values are assigned to the emergency rescue plan to provide various emergency rescue strategies for decision-makers.

Table 5. Statistical results of two objective functions with different weight values

Rescue area	(f_1, f_2)	$w_1 = 0.1$	$w_1 = 0.3$	$w_1 = 0.5$	$w_1 = 0.7$	$w_1 = 0.9$
A_1	(64.5,3205.94)	0.1	0.3	0.5	0.7	0.9
	(67, 2525.47)	0.59	0.5257	0.669	0.741	0.813
	(76.6, 2034.1)	0.785	0.670	0.555	0.440	0.324
	(81, 1815.9)	0.9	0.7	0.5	0.3	0.1
A_2	(60.9, 2722.07)	0.1	0.3	0.5	0.7	0.9
	(62.1, 1538.03)	0.931	0.927	0.923	0.919	0.915
	(74.3, 1522.77)	0.854	0.670	0.487	0.304	0.121
	(74.7, 1453.27)	0.9	0.7	0.5	0.3	0.1
A_3	(81, 2819.73)	0.1	0.3	0.5	0.7	0.9
	(82.7, 1878.59)	0.914	0.917	0.918	0.920	0.922
	(103.1,1788.2)	0.9	0.7	0.5	0.3	0.1

The bold values in Table 5 represent the maximum comprehensive preference index, and the corresponding Pareto solutions are the compromise solutions of this paper's dual-objective optimization problem. If the decision maker is more concerned about shortening the rescue time, he can choose a solution with a larger weight value of the objective function f_1 and a smaller objective function f_2. If the decision maker is more concerned about the rescue priority order, so that the disaster sites with serious disaster conditions are rescued first, he can give a solution with a larger weight value of the objective function f_1 and a smaller objective function f_2. If the decision maker wants to save rescue time and also wants to carry out rescue work according to the priority rescue order, the objective function f_1 and f_2 can be given the same weight value, these compromise solutions provide decision support for casualty rescue vehicle scheduling.

5. CONCLUSIONS

In this paper, the optimization of rescue vehicle and transfer route for the wounded in multi-disaster areas is studied. The number of injured people at the disaster point, the distance from the disaster point to the rescue center and the time when the rescue vehicle arrives at the disaster point are taken as the priority rescue level of the disaster point. Compared with the literature that simply determines the priority level of rescue based on the injury degree of the wounded, the method proposed in this paper takes into account the rescue timeliness, the different needs of the wounded, the distance factor, etc., which can shorten the rescue time more efficiently and reduce the casualties. At the same time, it is put forward that different treatment methods should be adopted for the wounded with different degrees of injury, and first aid should be given to the middle and severe wounded after simple treatment, so as to greatly improve the utilization ratio of emergency rescue resources.

Based on the limited background of rescue vehicles, this paper establishes a multi-objective mixed integer programming model for multiple rescue centers, with the shortest total rescue time and the smallest priority rescue weight as the optimization objectives, which are solved by using an iterative exact ε-constraint algorithm method. In order to get a quick solution, the second solution method is proposed, and a sub-problem of this problem, namely, the vehicle routing problem with multiple single rescue centers, is studied. The results of a case study show that both of the proposed methods can effectively solve the problem of post-earthquake casualty transfer and rescue vehicle scheduling. In addition, the solutions obtained by the a-constraint method are all better than the firefly algorithm, with higher quality and more solutions. The two-stage heuristic algorithm solves more efficiently than the firefly algorithm. Finally, the results of the experiment put forward relevant management suggestions for emergency departments, help decision-makers to make rescue plans, and guide the emergency center to set up a reasonable number of casualty rescue vehicles.

However, this study does not take into account the dynamic change of casualty status over time in post-disaster rescue and other rescue facilities. The follow-up study should add to the dynamic changes of casualty status over time and other rescue facilities such as helicopters and unmanned aerial vehicles (UAVs) participating in rescue, so that the model is more in line with the actual situation of large-scale wounded rescue after the earthquake.

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