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A study on the route planning of aviation emergency rescue considering disaster victims splitting according to backpacks

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ABSTRACT

In the emergency response phase after a natural disaster, aviation emergency rescue is an efficient means of rescue work. In this paper, the disaster victims to be rescued are discretely split according to the degree of injury, and different rescue time windows are given for each degree of injured disaster victims. The model takes into account helicopter performance factors such as capacity, cruise, hover, and fuel consumption, as well as the problem of multi-trip helicopter missions due to the scale of the emergency, with the decision objective of minimizing rescue delay loss. A genetic algorithm based encoding of virtual rescue points is developed to solve the problem, and the genetic operation of the algorithm is optimized to provide better solution performance for the model characteristics. Finally, the model and algorithm are validated with a real case, and comparative and sensitivity analyses are also performed.

1. Introduction

In recent years, the frequent occurrence of natural disasters has posed a serious threat to people's lives and has raised concerns about emergency response measures (Wang, Choi, Liu, & Yue, 2018). The level of emergency management after a disaster is critical to human safety and health (Liu, Li, Tu, & Zhang, 2011), and disaster decision-makers should be equipped with robust and generic tools and models to effectively handle rescue work (Barbarosoğlu & Arda, 2004). If the response is not properly handled, the disaster cannot be controlled in a timely and effective manner, which can seriously affect the recovery of social functions (Liu, Wang, & Li, 2022), this further highlights the importance that governments place on disaster response (Yang, Hao, & Lu, 2018).

Although technological advances have provided some technical support for early warning of natural disasters, accurate predictive capabilities are still not achievable and natural disasters around the world continue to pose a significant threat to the functioning of society. In 2005, Hurricane Katrina hit New Orleans in the United States and delays in treating disaster victims caused additional casualties (Lei, Pinedo, Qi, Wang, & Yang, 2015). In another natural disaster event, on 7 February 2009, more than 400 bushfires swept through parts of rural Victoria, Australia, killing 173 people and injuring 414 others (Lee, Lei, Pinedo, & Wang, 2013). In the aftermath of a natural disaster, infrastructure is almost destroyed within minutes or even seconds, houses collapse, roads are blocked, communications are disrupted, basic supply capabilities such as water and electricity are greatly affected and people in the affected areas are in desperate need of relocation to receive proper medical assistance.

Natural disasters are often accompanied by harsh geographical and weather conditions, and in some cases, road rescue can be inefficient due to traffic congestion or even disruptions to the transport network during vehicle transport, especially for rescuing disaster victims stranded in mountainous areas, where the rugged and complex terrain can greatly affect rescue efforts and cause delays in rescue times. In contrast, efficient aviation rescue has become the preferred option for special rescue missions. Helicopters have many advantages such as fast response time and no need for runways for take-off and landing (Abdelgader, Wu, & Nasr, 2016), and have already completed many emergency rescue missions in many countries (Andruszkow, Schweigkofler, Lefering, Frey, Horst, Pfeifer, Beckers, Pape, & Hildebrand, 2016). However, as a complex systems engineering task, aviation rescue is a technically demanding and collaborative operation (Zhang, Yu, Yu, & Zhang, 2016), including several tasks such as weather monitoring, organizational decision-making, and security, and is subject to restrictions such as fuel and landing and take-off environments, leading to many difficulties in helicopter emergency scheduling.

The devastation of a disaster can also lead to varying degrees of injury to disaster victims. In this study, disaster victims are split

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according to their degree of injury and an aviation emergency rescue route planning problem is posed in which disaster victims are divided according to backpacks, which is defined as the smallest set of needs that cannot be further divided. In this study, people with different levels of injury are considered as individual backpacks with different rescue time windows.

This study can develop an aviation emergency rescue route planning model with backpacks splitting characteristics from two perspectives: mission scenario and aviation rescue, the model can solve the problem of aircraft scheduling in the event of natural disasters. The paper is organized as follows. In Section 2, we review the literature that is relevant to this study. In Section 3, we develop an aviation emergency rescue route planning model that characterizes the problem of this paper, In Section 4, we develop a genetic algorithm suitable for solving the model. In Section 5, the problem and algorithm presented in this paper are validated based on a practical case. The final section contains the conclusions and the discussions for future work.

2. Related work

2.1. Vehicle routing problem

2.1.1. Split delivery vehicle routing problem

In a standard Vehicle Routing Problem (VRP), the capacity of the vehicle is greater than the demand of any customer. However, in reality, there are situations where some customers have high demand, especially emergency demand, when some demand points require multi-vehicle deliveries. This has led to the Split Delivery Vehicle Routing Problem (SDVRP). Archetti, Feillet, Gendreau, and Speranza (2011) studied the complexity of the SDVRP problem and confirmed that when the loading capacity of a vehicle increases (relative to the demand units), the SDVRP is an NP-hard problem. Ji, Zhou, Yu, and Wu (2021) proposed a two-dimensional loading constrained split delivery vehicle routing problem (2L-SDVRP) model. Wang, Kinable, and van Woensel (2020) applied SDVRP to the fuel supply problem and solved it for multi-vehicle, multi-trip, and sub-contract deliveries. Yang, Wang, Pang, Tan, and Zhou (2020) considered the case of goods being consumed during transportation under adverse conditions. Regarding the solution of SDVRP, the Branch-and-Cut-and-Price algorithm by (Archetti, Bianchessi, & Speranza, 2014) and the method based on the new vehicle exponential flow formula proposed by Ozbaygin et al are the strongest exact methods available (Ozbaygin, Karasan, & Yaman, 2018), but these exact methods can only solve small instances, so solving SDVRP mostly uses heuristic algorithms, including neighborhood search algorithm (Ji et al., 2021), ant colony algorithm (Yang et al., 2020), genetic algorithm (Zeng, Wang, Chen, & Yang, 2021), etc.

Most of the current research on SDVRP has been on the continuous splitting of demand, where vehicles can be loaded with any number of units at the demand point. Qiu, Fu, Eglese, and Tang (2018) considered the case of discrete splitting, splitting demands into bags, and verified that the splitting method could reduce travel costs by combining experiments with different batches. Gupta, Govindan, Mehlawat, and Khaitan (2022) applied this splitting method to the green vehicle routing problem and considered the case of uncertainty in travel time, minimizing fuel emissions by modeling and solving for it. There is less research on discrete split vehicle route problem (Salani & Vacca, 2011), the aforementioned studies did not consider the individual demand time variability of splitting objects, especially for emergency demands. As far as we know, different time windows have not been considered for emergency demands in currently discrete splitting studies.

2.1.2. Vehicle routing problems with multiple time windows

Vehicle Routing Problems With Multiple Time Windows (VRPMTW) are those where the customer requests a service that can be over a range of time periods. Belhaiza, Hansen, and Laporte (2014) designed a hybrid variable neighbourhood forbidden search method to solve the VRPMTW, and the study also developed a relaxation algorithm. Baradaran, Shafaei, and Hosseinian (2019) presented the vehicle distribution problem for heterogeneous vehicles with multiple hard priority time windows (VRPMPTW) and developed three multi-objective models considering uncertainties. Beheshti, Hejazi, and Alinaghian (2015) also considered the problem of multiple priority time windows and developed a co-evolutionary multi-objective quantum genetic algorithm. Favaretto, Moretti, and Pellegrini (2007) considered the vehicle path problem with multiple time windows with periodic constraint properties and designs an ant colony algorithm for solving it.

Most of the current research on VRPMTW defines that demand points can have different delivery times, where vehicles can deliver goods within a specified time period, give a certain penalty for not being within the time period (soft time window) or simply not allow delivery (hard time window). Under emergency demand conditions, the variability of the individuals being rescued may lead to different levels of urgency of the demand and therefore different time windows for rescue, and this case can also trip the multiple time window problem. Currently, the time window for most VRPMTW studies is set at the time of service to the point of need, but for emergency relief, it is the time to transfer the victims to a shelter or hospital that affects the final outcome of the relief.

2.2. Emergency route planning problem

Unlike the traditional logistics industry of vehicle routing problem, emergency rescue is often characterized by strong timeliness and weak economy. At the same time, emergency demands are more complex. Disasters can also lead to changes in weather and road conditions, making the transport time of emergency vehicles difficult to determine, or even causing road blockages and resulting in routing failures. At present, research into emergency route planning has been conducted mainly from two perspectives: demand and uncertainty.

Based on the diversity of emergency demands, Bodaghi, Palaneeswaran, and Abbasi (2018) considered both expendable resources (food, tents, etc.) and non-expendable resources (volunteers, doctors, etc.), loaded them into the same vehicle for transportation, and set the disposal time at the point of need as a decreasing linear function of the amount of non-expendable resources. Sheu (2010) proposed a dynamic rescue demand management model for emergency logistics operations under conditions of incomplete information about large-scale natural disasters, and applied data fusion to predict rescue demand in multiple regions. Fontem, Melouk, Keskin, and Bajwa (2016) considered the problem of network delivery in the presence of uncertainty in travel times and deadlines. Jiang, Bian, and Liu (2021) studied the optimization of emergency supplies of fresh agricultural products in the context of a large-scale pandemic. The optimization model considered response time, risk of infection and transport resources. Zhang, Qin, Wang, He, and Liu (2017) proposed the manpower allocation and vehicle routing problem (MAVRP), a model that optimizes both manpower allocation and vehicle routing, based on the real-life medical problems derived from non-emergency ambulance transfer services in public hospitals in Hong Kong. Anuar, Lee, and Pickl (2022) studied the delivery of critical supplies in humanitarian operations and the model considered random road capacity and damage. Chen, Pan, Chen, and Liu (2020) proposed a vehicle distribution problem for a non-contact joint distribution service during the COVID-19 epidemic.

For emergency rescue, the destructive nature of disasters can cause varying degrees of harm to people. When assessing a disaster, it is important to focus not only on the extent of the disaster, but also on the consequences of the disaster. The varying degrees of injury of disaster victims requiring rescue creates a diversity of emergency demands. The urgency of rescuing disaster victims with different levels of injury at the same rescue point also varies.

2.3. Aviation emergency rescue areas

The salient feature of emergency route planning is the variability of the mission environment, resulting in a high degree of uncertainty in factors such as travel time. Compared to road emergency response, aviation emergency rescue is relatively less dependent on geographical conditions, and parameters such as speed are relatively easy to determine, but the characteristics of helicopter bring with them other factors and limitations. In aviation emergency rescue missions, the low altitude operating environment of aircraft operating below 1000 m often suffers from high safety risks, low rescue efficiency and unreasonable implementation due to helicopter performance.

Based on the perspective of aircraft scheduling optimization, Ono et al. (2013) investigated the differences in aircraft response intervals for the provision of emergency medical services in different situations. Zhang, Li, and Li (2021) developed a collaborative air-ground dispatch model that considered the traffic environment and the performance of different aircraft. Chen et al. (2022) proposed a three-tier network model for cross-regional emergency resource dispatching, in which the three-tier multi-model network is formed by the superposition of railway, road, waterway, and air networks. Ferrari and Chen (2020) saw air search and rescue fleet planning as a resource allocation problem. Zhang et al. (2016) considered the effect of stochastic wind speed in the optimization of an aviation emergency rescue route and constructed a scheduling optimization model incorporating maximum fuel load, average fuel consumption per hour, and aircraft cruise flight speed.

Based on the aviation emergency rescue capability assessment, Zhang, Hu, and Li (2019) evaluated general aviation emergency rescue capabilities, using performance parameters such as helicopter range, hovering, and load as key influencing factors. Sun, Liu, Tian, Wu, and Gao (2020) applied virtual reality technology to evaluate the effectiveness of helicopter emergency rescue. From the perspective of search and rescue task allocation. Zhang, Li, Wang, Li, and Li (2022) constructed a search and rescue task allocation model by considering factors such as the UAV operating environment and hovering endurance. Beck, Teacy, Rogers, and Jennings (2018) constructed a collaborative online planning problem model for search and rescue disaster victims' work in emergency response.

From the above literature, it can be concluded that the performance of aircraft is the most critical element for research related to aviation emergency rescue, mainly comprising cruise speed, fuel consumption, hovering, and loading capacity. For large-scale emergency operations, helicopters are in relatively short supply compared to road-based emergency vehicles, when multiple round trips are required to carry out rescue missions with minimal pilot fatigue.

3. Model formulation for aviation emergency rescue route planning

3.1. Problem description

In this study, the problem focuses on the use of helicopters for the emergency task of rescuing injured disaster victims. Some of the rescue points do not have normal landing and take-off conditions due to the limitations of the slope, hardness of the ground, and extreme geographical conditions, and therefore required the use of electric winches for hovering rescue work with the cooperation of winch hands and lifeguards. The number of disaster victims waiting to be rescued at some of the rescue points exceeds the helicopter's capacity, allowing disaster victims at the same rescue point to be transferred in batches, but disaster victims with the same level of injury at the same rescue point need to be transferred in the same batch. Due to the scale of the mission and the number of helicopters, each helicopter has to make several trips between the hospital and the rescue point until all the disaster victims had been transferred to the hospital. The fuel consumption coefficient differs between cruising and hovering helicopters, especially when hovering, where the helicopter uses its tail to counteract the counter-torque caused by the rotor blades to keep the helicopter stable in the air, resulting in additional fuel consumption. Disaster victims with different injuries require different resettlement times and have different rescue time windows. The rescue mission scenario is shown in Fig. 1.

3.2. Problem assumptions

The following assumptions underlie the model in this study.

Assumption 1. Emergency helicopters are deployed at the base in advance and are in airworthy condition, and all helicopters depart from the base in unison at the start of the mission.

Clarification: As the activation of the helicopters is a relatively time-consuming task, the aviation emergency rescue team will do a good job of preparation before the emergency occurs to ensure that the helicopters are in an airworthy condition at all times, and that all these preparations have been deployed in advance before the decision maker gives the order to deploy the mission.

Assumption 2. Accessibility is provided between each node and the flight time of the helicopter between the nodes is known.

Clarification: Unlike road rescue, helicopter rescue is less dependent on geography, so the paper defaults to helicopters being able to fly between any node.

Assumption 3. The number of disaster victims waiting to be rescued at each rescue point and the number of people at each injury level is known, the number of people at each injury level after splitting is less than the emergency helicopter capacity.

Clarification: The paper divides the disaster victims according to the degree of injury, and proposes a route planning problem that divides the disaster victims according to backpacks, which is defined as the minimum set of demands that cannot be further divided. In this study, the groups with different degrees of injuries are considered as individual backpacks, so that the number of disaster victims who need to be transferred to the same affected demand point is a discrete combination of multiple backpacks, and any backpack is smaller than the capacity of the helicopter. This also ensures that the helicopter can continuously load multiple backpacks.

Assumption 4. The emergency helicopter used for the rescue mission is of the same type.

Clarification: Different types of helicopters are used for different emergency work scenarios, this paper is a study of helicopter rescue and transfer of disaster victims. Therefore, it is assumed that the same helicopters are deployed at the same base for the evacuation of the disaster victims.

Assumption 5. Time spent by the helicopters in refueling is negligible, while not taking into account queuing issues. Negligible time spent on the ground for normal take-off and landing to accommodate and unload the disaster victims.

Clarification: In this study, the rescue time is mainly determined by the helicopter cruise flight time as well as hover rescue placement time. Generally, large helicopters used for rescue transportation missions have a long range and require less frequent refueling and a short refueling time, while the number of refueling equipment at the default resupply point can meet the refueling needs of any number of helicopters. Therefore, the refueling time for helicopters is negligible. And in the normal execution of ground rescue placement or arrival at the hospital to unload the disaster victims, there is no need to use the electric winch for operation.

3.3. Mathematical model

$$min f = \sum_{k\in K}\sum_{v\in V}\sum_{r\in R}\left(b_r \max\left\{T^{kv} - tm_r, 0\right\}\sum_{i\in N_b} Y_{ir}^{kv} C_i^r\right) \tag{1}$$

Subject to:

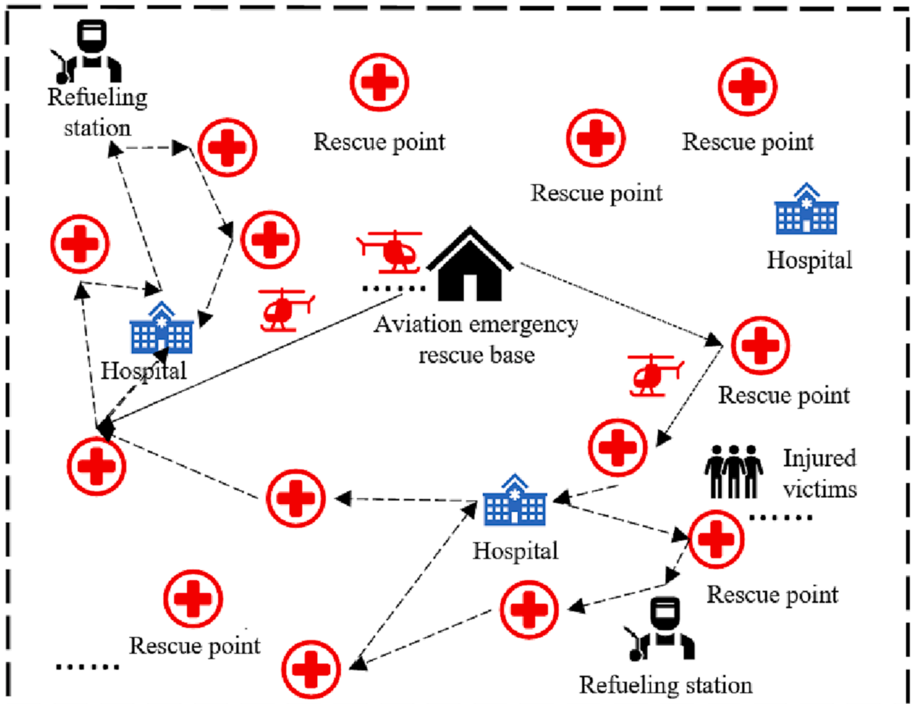

Fig. 1. Aviation emergency rescue mission scenario.

$$\sum_{v\in V}\sum_{k\in K}H_i^{kv}\geqslant 1,\forall i\in N_b \tag{2}$$

$$\sum_{k\in K}\sum_{v\in V}Y_{ir}^{kv}=1,\forall i\in N_b,\forall r\in R \tag{3}$$

$$H_i^{kv}=\max_{\forall r\in R}\{Y_{ir}^{kv}\},\forall i\in N_b,\forall k\in K,\forall v\in V \tag{4}$$

$$\sum_{j\in N_b\cup N_c}X_{0j}^{kv}=1,v=1,\forall k\in K \tag{5}$$

$$\sum_{i\in N_c}\sum_{j\in N_b\cup N_d}X_{ij}^{kv}=1,v\in V\backslash 1,\forall k\in K \tag{6}$$

$$\sum_{i\in N_b\cup N_d}\sum_{j\in N_c}X_{ij}^{kv}=1,\forall v\in V,\forall k\in K \tag{7}$$

$$\sum_{i\in N\backslash N_c}X_{ij}^{kv}=H_j^{kv},v=1,\forall j\in N_b,\forall k\in K \tag{8}$$

$$\sum_{j\in N\backslash N_a}X_{ij}^{kv}=H_i^{kv},v=1,\forall i\in N_b,\forall k\in K \tag{9}$$

$$\sum_{i\in N\backslash N_a}X_{ij}^{kv}=H_j^{kv},v\in V\backslash 1,\forall j\in N_b,\forall k\in K \tag{10}$$

$$\sum_{j\in N\backslash N_a}X_{ij}^{kv}=H_i^{kv},v\in V\backslash 1,\forall i\in N_b,\forall k\in K \tag{11}$$

$$\sum_{i\in N_b\cup N_d}X_{ij}^{kv}=\sum_{h\in N_b\cup N_d}X_{jh}^{k(v+1)},\forall j\in N_c \tag{12}$$

$$\sum_{i,j\in N_b}X_{ij}^{kv}\leqslant|\phi|-1,\forall k\in K,\forall v\in V \tag{13}$$

$$C_i=\sum_{r\in R}C_i^r,\forall i\in N_b \tag{14}$$

$$\sum_{i\in N_b}C_i\leqslant v_{\max}w \tag{15}$$

$$Z_i^{kv}=\sum_{r\in R}Y_{ir}^{kv}C_i^r,\forall i\in N_b,\forall k\in K,\forall v\in V \tag{16}$$

$$\sum_{k\in K}\sum_{v\in V}Z_i^{kv}=C_i,\forall i\in N_b \tag{17}$$

$$\sum_{i\in N_b}Z_i^{kv}\leqslant w,\forall k\in K,\forall v\in V \tag{18}$$

$$Wt_i^{kv}=\sum_{r\in R}Y_{ir}^{kv}C_i^r(fe_r\max\{\gamma_i,0\}),\forall i\in N_b,\forall k\in K,\forall v\in V \tag{19}$$

$$T^{k(v+1)}=T^{kv}+\sum_{i\in N}\sum_{j\in N}X_{ij}^{kv}tr_{ij}+\sum_{i\in N_b}Wt_i^{kv},\forall k\in K,\forall v\in V \tag{20}$$

$$P_{i2}^{kv}=u,\forall i\in N_a\cup N_d,\forall k\in K,\forall v\in V \tag{21}$$

$$P_{j1}^{kv}\leqslant P_{i2}^{kv}-\delta^\alpha tr_{ij}+M\left(1-X_{ij}^{kv}\right),\forall i,j\in N,\forall k\in K,\forall v\in V \tag{22}$$

$$P_{i2}^{kv}=P_{i1}^{kv}-Wt_i^{kv}\delta^\beta\max\{\gamma_i,0\},\forall i\in N_b,\forall k\in K,\forall v\in V \tag{23}$$

$$P_{i1}^{kv}=P_{i2}^{k(v+1)},\forall i\in N_c,\forall k\in K,\forall v\in V \tag{24}$$

$$P_{i1}^{kv}\geqslant\rho u,\forall i\in N,\forall k\in K,\forall v\in V \tag{25}$$

Objective (1) is to minimize rescue delay loss. The decision objective takes into account the urgency of rescue for disaster victims with different levels of injury, and the loss function is related to the time it takes for disaster victims to be transferred to the hospital and the number of people transferred. There is no reward for arriving earlier than the time window, but there is a penalty for arriving later than the rescue time window. The greater the degree of injury to the disaster victims, the larger the penalty coefficient (Table 1).

The constraints can be summarized as the helicopter access node

Table 1
A summary of notations.

Notation	Definition
Sets	
N_a	Aviation emergency rescue base, $N_a = \{0\}$
N_b	Set of rescue points, $N_b = \{1, 2, \cdots, n\}$
N_c	Set of designated hospitals, $N_c = \{n+1, n+2, \cdots, n+m\}$
N_d	Set of refueling stations, $N_d = \{n+m+1, n+m+2, \cdots, n+m+h\}$
N	Set of all nodes, $N = N_a \cup N_b \cup N_c \cup N_d$
K	Set of emergency helicopters, $K = \{1, 2, \cdots, k\}$
R	Set of injury rating of the disaster victims, $R = \{1, 2, \cdots, r\}$
V	Set of emergency helicopter trips, $V = \{1, 2, \cdots, v\}$
Indexes	
i	Helicopter access to the node index
j	Helicopter access to the node index
k	Emergency helicopters index, $k \in K$
r	Disaster victims injury rating index, $r \in R$
v	Emergency helicopter trip index, $v \in V$
Parameters	
w	Maximum number of disaster victims that can be loaded on an emergency helicopter k
c_i^r	Number of disaster victims with injury level r at rescue point i
c_i	Total number of disaster victims to be relocated at rescue points i
γ_i	If emergency helicopter at rescue point i settles disaster victims with hover rescue, γ_i=1; otherwise, γ_i=0
fe_r	Disposal time of disaster units with injury class r at the time of the hover rescue
tr_{ij}	Cruise flight time of helicopter from node i to j
tm_r	The rescue time window for disaster victims with injury level r to reach the hospital
b_r	Delayed loss of rescue per injured disaster victims per unit of time for r
u	Fuel tank volume for emergency helicopters
δ^α	Fuel consumption coefficient for helicopter cruising flights (at a certain cruising speed)
δ^β	Fuel consumption coefficient for the hovering rescue phase of a helicopter (at a given hover height)
v_{max}	Maximum number of trips per emergency helicopter
ρ	Safe backup fuel coefficient(contingency fuel) for emergency helicopters
M	A large number
Variables	
X_{ij}^{kv}	If emergency helicopter k visits node j from node i for the trip v, X_{ij}^{kv}=1; otherwise, X_{ij}^{kv}=0
Y_{ir}^{kv}	If the emergency helicopter k is loaded on its trip v with disaster victims of rescue point i of injury level r, $Y_{ir}^{kv} = 1$; otherwise, $Y_{ir}^{kv} = 0$
H_i^{kv}	If emergency helicopter k visits rescue point i on the trip v, $H_i^{kv} = 1$; otherwise, $H_i^{kv} = 0$
Wt_i^{kv}	Disposal time of emergency helicopter k for the trip v at rescue point i
T^{kv}	Emergency helicopter k time to complete the trip v
Z_i^{kv}	Number of disaster victims loaded at rescue point i on the trip v of emergency helicopter k
P_{i1}^{kv}	The amount of fuel remaining in the tank of the emergency helicopter k for the trip v to node i
P_{i2}^{kv}	The amount of fuel remaining in the tank of the emergency helicopter k leaving node i on trip v

constraint, the helicopter capacity constraint, the travel time constraint, and the helicopter fuel constraint.

1) Node access constraints

Eq. (2) indicates that each rescue point can be visited by multiple helicopters on different trips. Eq. (3) indicates that disaster victims with the same level of injury at each rescue point cannot be further split. Eq. (4) indicates that if a helicopter visits a rescue point on a given trip, it must be loaded with disaster victims with a certain level of injury at that rescue point. Eq. (5) indicates that all helicopters depart from the base on the first trip. Eq. (6) means that the helicopter departs from the hospital at the beginning of all trips except the first. Eq. (7) means that disaster victims are taken to the hospital at the end of each trip. Eqs. (8) to (11) represent the conservation of flow per helicopter per trip. Eq. (12) represents the articulation of successive trips of the same helicopter. Eq. (13) avoids the formation of sub-loops between rescue points.

2) Capacity constraints

Eq. (14) indicates that the total number of disaster victims waiting to be rescued at each rescue point is equal to the sum of the number of disaster victims at each level of injury. Eq. (15) ensures that all disaster victims are rescued. Eq. (16) means that the number of people loaded on the helicopter at the rescue point is the sum of the number of people loaded for each level of injury. Eq. (17) indicates that all injured people at the rescue points need to be rescued. Eq. (18) indicates a limit on the number of people the helicopter can load per trip.

3) Travel time constraint

Assuming a departure time of 0 for all helicopters, the cumulative flight time of the helicopters consists of the cruise flight time and the resettlement time of the disaster victims. The resettlement time is only affected by the hover rescue. Eq. (19) indicates the time required for the helicopter to settle the disaster victims at the rescue point. Eq. (20) indicates the completion time of each helicopter trip.

4) Fuel constraint

Eq. (21) indicates that the helicopter is fully fuelled when leaving either the base or the refueling point. Eq. (22) indicates the cruise flight fuel consumption. Eq. (23) indicates the fuel consumption at the rescue point. Eq. (24) indicates the fuel inheritance relationship between the front and rear trips of the helicopter. Eq. (25) ensures that the helicopter arrives at each node with a greater amount of fuel than the backup fuel.

4. Design of genetic algorithm

Route planning is a classical combinatorial optimization problem, and the difficulty of solving the problem increases dramatically as the size of the problem increases. Genetic algorithm, as a relatively mature intelligent optimization algorithm, has been widely used to solve combinatorial optimization problems (Gupta et al., 2022). Therefore, a maximum retained crossover and adaptive mutation genetic algorithm (MRC&AM-GA) has been developed in this paper to solve the model, the algorithm uses a new encoding method based on virtual rescue points. The main design steps of the algorithm are encoding, decoding, fitness calculation, and genetic operation.

4.1. Coding method

Assuming that the helicopters need to visit a total of n rescue points, and the disaster victims to be rescued at each rescue point are split into a total of r injury levels, then the helicopter needs to pass through n*r virtual nodes after visiting all the rescue points. The numbers from 1 to n*r are not the actual rescue point numbers in the model, but are the definition of virtual rescue point, which also constitute the backpacks in this paper. The virtual rescue point code is shown in Fig. 2.

In the encoding method of other nodes, 0 represents the base, H represents the hospital, and R represents the refueling point.

4.2. Decoding strategy

The decoding operation is carried out in four steps: determining the helicopter trips, the adjustment of backpacks within the trip, the insertion of hospital nodes, and the selection of fuel supply points. Firstly, the helicopter trip is determined by cutting to determine the virtual rescue point visited by each helicopter for each trip. Secondly, the location of

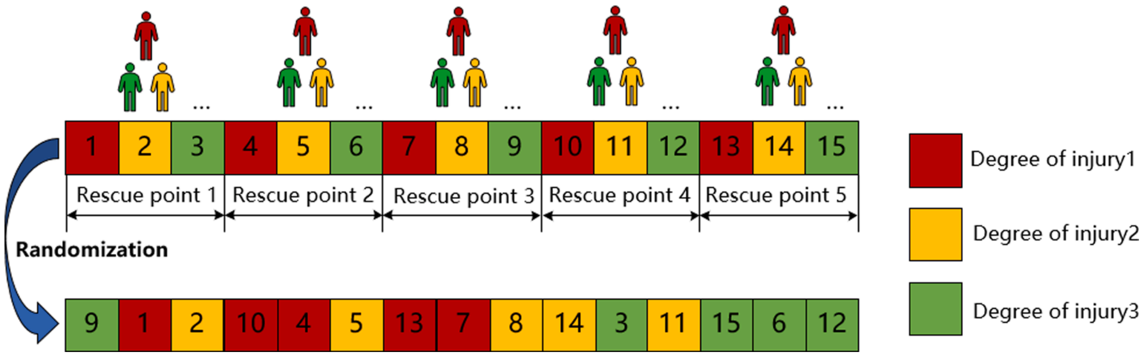

Fig. 2. Virtual rescue point coding method.

the backpacks within the trip is adjusted. Thirdly, identify suitable hospitals to house the disaster victims based on the head and end rescue points of each trip. Finally, based on the characteristics of helicopter fuel replenishment, refueling strategies are developed and suitable fuel supply points are inserted, resulting in a complete helicopter route plan.

4.2.1. *Trip cutting*

In this study, a putback random sampling method is used to select the cut points and the number of cut routes depends on the number of helicopters and the maximum number of trips. Although the maximum number of trips per helicopter is specified in the model, however, when helicopters are on a rescue mission, each helicopter does not necessarily need to run all trips and only needs to meet the need to move all disaster victims. Therefore, when decoding the cut trips, the same cut point is chosen to indicate that the trip access node belonging to that helicopter is the empty set, i.e., the helicopter does not perform this trip task. In the final formed cut piece segment, according to left-to-right order, each $v_{\max}$ is a route plan for one helicopter.

4.2.2. *Backpacks adjustment*

As disaster victims at the same rescue point are split into backpacks and have different time windows, disaster victims with different levels of injury at the same rescue point can theoretically be transferred in multiple batches, which results in different backpacks belonging to the same rescue point within the same trip of a particular helicopter being able to be randomly arranged in a sequence of routes, not necessarily in adjacent order. Once the trip route has been determined, if the different backpacks belonging to the same rescue point are not in adjacent order, they need to be adjusted to be in adjacent order.

4.2.3. *Hospital selection*

At the end of each trip, the helicopter needs to place the disaster victims in a suitable hospital for treatment, thus freeing up seats for the next rescue mission. The hospital visited at the end of a helicopter trip is also the starting point for the next trip. Therefore, the hospital with the shortest distance between the last rescue point of the current trip and the first rescue point of the next trip is used as the endpoint of the current trip. When the helicopter performs its last trip, it only needs to select the hospital with the closest distance to the last rescue point visited on this trip.

4.2.4. *Fuel replenishment*

The fuel replenishment point selection scheme of this study can be described as follows: when the helicopter arrives at the actual node corresponding to gene at i, calculate the remaining fuel for the executable mission (removal of backup fuel), calculate the fuel consumption of the cruise flight to the next actual node corresponding to gene at $i+1$ according to the order of the route node visits, then calculate the fuel consumption resulting from the resettlement of disaster victims at the node corresponding to gene at $i+1$, and finally calculate the fuel consumption from the actual node corresponding to gene at $i+1$ to the nearest refueling node. Compare the remaining executable task fuel with the sum of the three fuel consumptions above, If the former is greater than the latter, the helicopter still has enough fuel to travel to the replenishment point after flying to the actual node corresponding to gene at i and placing the disaster victims, so there is no need to insert a refueling node after gene at i. If the former is less than the latter, the corresponding refueling node needs to be inserted to meet the next rescue mission.

Two cases need to be analyzed for inserting the refueling stations. When the actual nodes corresponding to gene at i and gene at $i+1$ belong to different nodes, then only the appropriate refueling station point needs to be inserted between the actual nodes corresponding to i and $i+1$; however, when the actual nodes corresponding to i and $i+1$ belong to the same rescue point, if the fuel refueling point is inserted between them, the helicopter returns to the original node after flying to the refueling station point to refuel, which means that when the helicopter finds that it is running low on fuel after resettling some of the disaster victims at the rescue point, it needs to refuel at the refueling point and come back to continue resettling the remaining victims at that rescue point. The fallback operation is performed for the sub-case, i.e., the actual node corresponding to i is selected to refuel and resupply in front of its different nodes, ensuring that the nodes before and after the refueling node visited by the helicopter are different.

After analyzing the specific scenario where refueling is needed, a suitable refueling site needs to be selected. In this paper, there are two options for selecting refueling stations for helicopters. The first scheme is to calculate the sum of the two visiting nodes of the helicopter before and after refueling among all refueling nodes, select the refueling station point with the smallest distance, and, when the remaining fuel of the helicopter at the current node can guarantee to reach the refueling node, choose to insert the refueling node; when the remaining fuel of the helicopter at the current node cannot guarantee to reach the refueling node, choose the refueling node closest to the node.

In Fig. 3, the specific implementation of each step in the decoding operation is illustrated. The example assumes that there are five rescue points, that the disaster victims at each rescue point are split into three levels according to the degree of injury, and that there are two helicopters performing emergency missions, each of which performs a maximum of two trip rescue missions. After implementing the rules for each step, two path scenarios are finalized. In scenario (a), both helicopters perform 2 trip missions, while in scenario (b), the second helicopter performs only one mission(The other trip is an empty set).

4.3. *Fitness function*

Since the routes generated after cutting do not necessarily comply with the helicopter capacity constraint, in this paper, solutions that violate the constraints are penalized. The fitness function is calculated as Eq. (26).

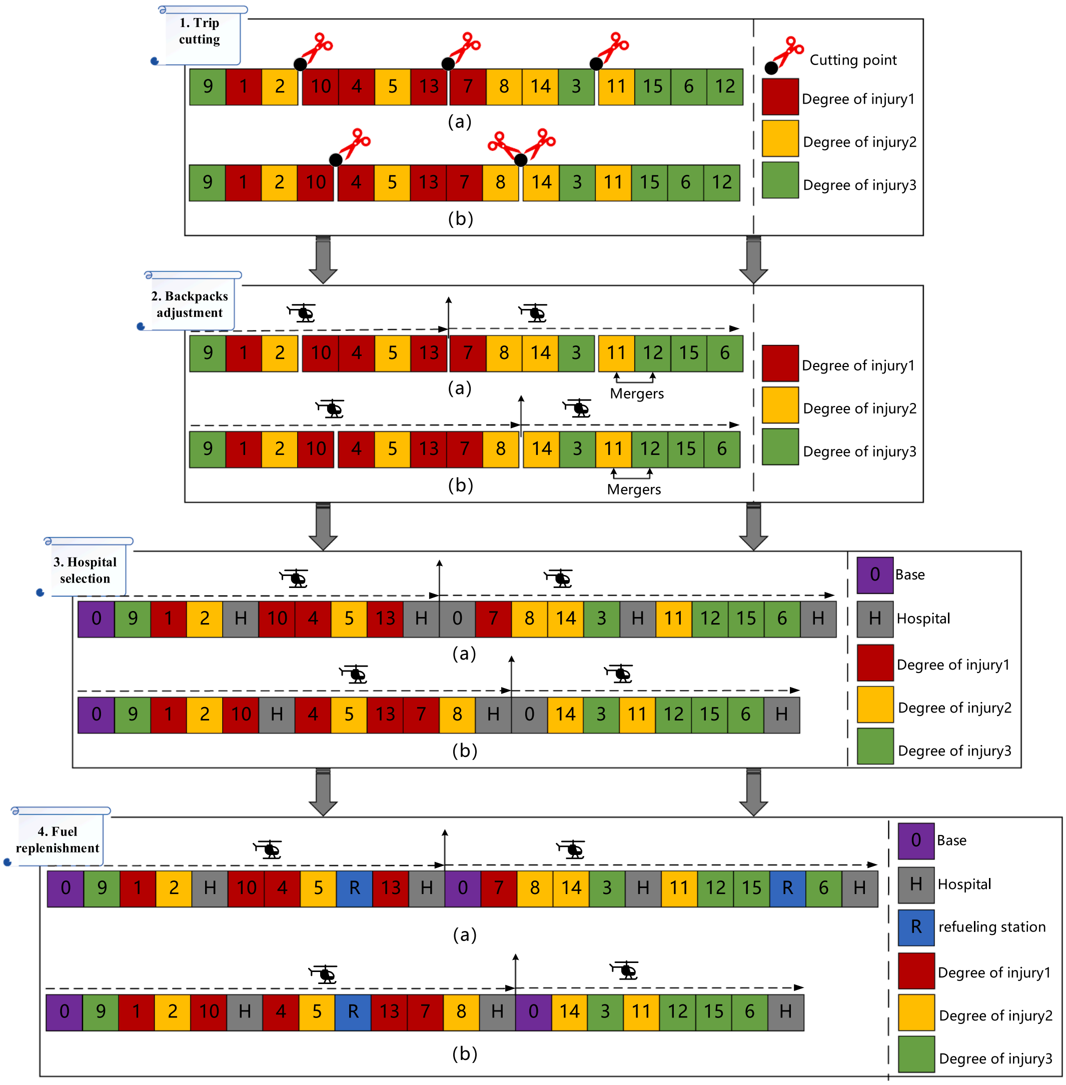

Fig. 3. Detailed steps of the decoding process.

$$\min f = \left(\sum_{k\in K}\sum_{v\in V}\sum_{r\in R}\left(b_r \max\left\{T^{kv} - tm_r, 0\right\}\sum_{i\in N_b} Y_{ir}^{kv} C_i^r\right) + M\sum_{k\in K}\sum_{v\in V}\max\left\{\sum_{i\in N_b} Z_i^{kv} - w, 0\right\}\right) \tag{26}$$

4.4. Genetic operation

4.4.1. Mixed selection strategy

The selection method used in this study is a combination of the binary tournament method and the retention of the elite strategy. The binary tournament method ensures that each individual in the population has a probability of being selected unless it is the least fit individual in the population, thus giving the algorithm a stronger global search capability. The retention of the elite strategy ensures that the individuals with the highest fitness degree in the population make it to the next generation without being eliminated. The individuals with the highest fitness degree in the current population are not subject to crossover and mutation operations and enter the offspring directly, replacing the individuals with the worst fitness degree in the offspring and ensuring convergence of the algorithm.

4.4.2. Maximum retained crossover

The two crossover approaches adopted in this study can provide a degree of assurance that the population is diverse and avoid generating too many structurally duplicated chromosomes. When the offspring chromosome is decoded, the selected subroutes (including empty trips) are not cut, but only the sequences formed by the remaining gene sets are cut. The number of cut fragments is equal to the total number of helicopter strokes minus the number of selected child routes. The cutting trips are spliced with the retained routes, in left-to-right order, each v_{max} is a route plan for one helicopter. The two crossover methods are shown in Fig. 4.

As the same offspring chromosome is decoded, different cut point selections can generate different routing trips, and the crossover operation does not guarantee that the offspring chromosomes are necessarily better than the parent chromosomes, therefore, the maximum retained crossover in this paper incorporates a multiple cut strategy, which performs multiple trip cuts based on the generated offspring chromosomes, while mixing the parent chromosomes and the multiple cut offspring chromosomes for the decoding operation, and selecting the individual with the highest fitness from the mixed population as the final crossover offspring.

4.4.3. Adaptive mutation operator

To enhance the local search capability at the later stage or when merit search stalls, this paper optimizes the mutation operation. The study defines the adaptive rule as follows:

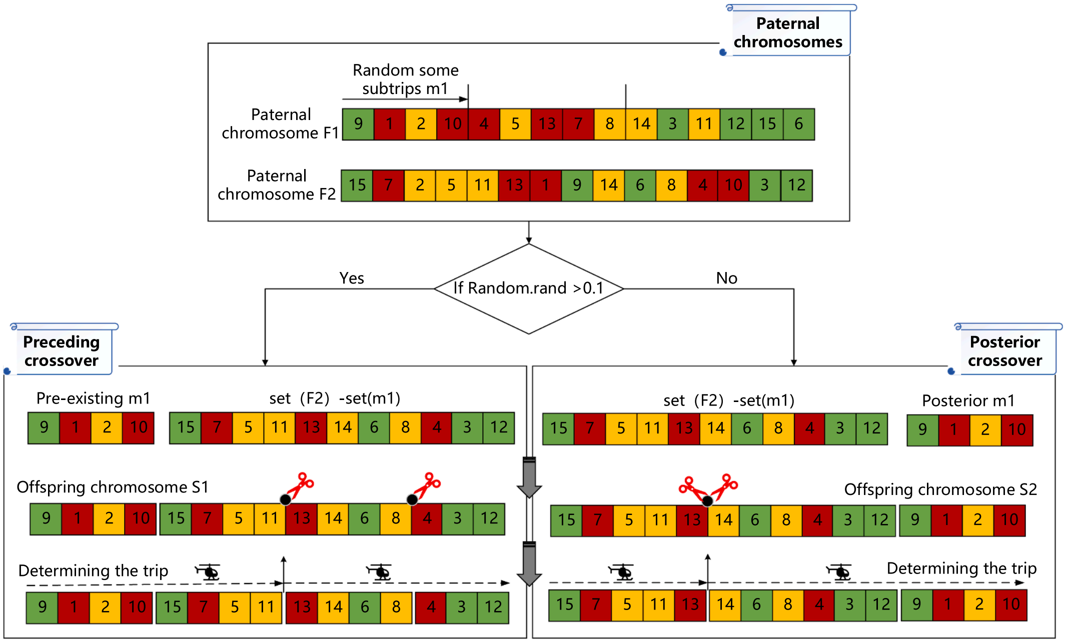

Fig. 4. Crossover operation.

$$P_{\max} = \begin{cases} P^1_{\max}, & bfit_n \leqslant \chi_{\max} \\ P^2_{\max}, & bfit_n > \chi_{\max} \end{cases} \tag{27}$$

$$p_m(k) = \begin{cases} P_{\max} \times \dfrac{3pop/2 - k}{pop}, & k \geqslant pop\Big/2 \\ P_{\max}, & k < pop/2 \end{cases} \tag{28}$$

In Eqs. (27) and (28),$P_{\max}$ is the mutation probability control parameter, whose value is determined according to the number of times the current optimal solution is maintained constant in the iterative process, and if the number of stagnation exceeds $\chi_{\max}$,$P_{\max}$ takes a larger value. k is the ordinal number of the population fitness of the offspring generated by the crossover operation sorted from smallest to largest, $p_m(k)$ denotes the mutation probability of the individual whose population fitness is sorted as k.

Ordinary 2-opt based mutation operation has performed poorly in solving this paper's model. In this study, we designed mutation strategies based on 2-opt and insertion. To avoid excessive splitting of the same rescue point, 2-opt in this paper has two implementation forms, namely, exchanging the selected backpacks and exchanging all the backpacks corresponding to the selected rescue point in the trip, two forms are randomly selected. The insertion operation can be described as: randomly selecting two backpacks or all the backpacks in the corresponding rescue point in the trip, and randomly performing forward

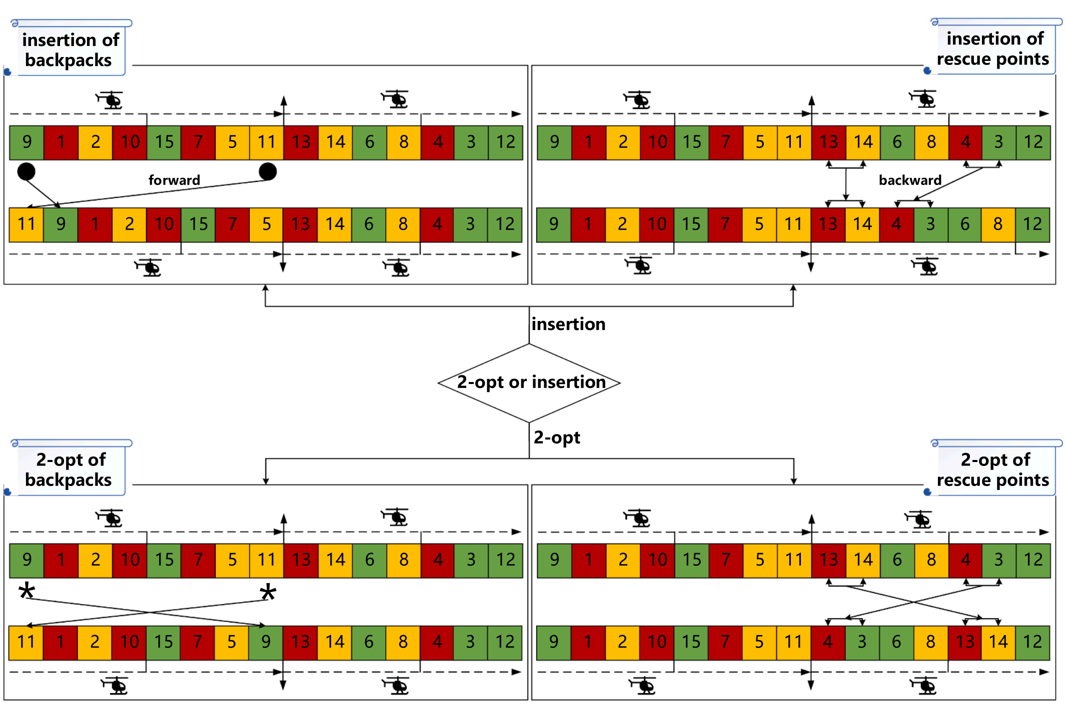

Fig. 5. Mutation operation.

insertion or backward insertion. The mutation operations were implemented randomly and executed multiple times, the next mutation operation is based on the previous one. The mutation can be accepted and stopped once the fitness is better than the offspring. But if the fitness becomes worse, the mutation result can still be retained with a relatively small probability. This method ensures a certain degree of local search in the direction of seeking superiority and increases the population diversity with a certain probability. The specific implementation of mutation operation is shown in Fig. 5.

5. Case study

5.1. Case background

Wenzhou City, Zhejiang Province, China, is prone to natural disasters due to its complex geographical conditions, posing considerable difficulty to rescue work. The city has established and gradually improved its aviation emergency rescue system since 2012, with the backbone of its aviation emergency rescue force being the East Sea First Rescue Flight of the Chinese Ministry of Transport, which is responsible for major natural disaster rescue work and provides emergency rescue services to units and individuals free of charge, with radiation coverage of the city and surrounding cities. The incoming Wenzhou aviation emergency rescue force is deployed at Longwan International Airport, equipped with several rescue helicopters and crews, each equipped with a winch. In carrying out special rescue tasks such as search and rescue at sea or rescue operations under extreme geographical conditions, winch handlers and lifeguards are required to use the winch control system to complete rescue placement in the hovering state of the helicopter. The city has now established a three-tier nodal rescue space layout of base-resupply point-landing point.

5.2. Data preparation

An aviation emergency rescue mission scenario is shown in Fig. 6. The location parameters of the rescue points are randomly generated and the parameters of the other nodes are derived from the existing configuration of the aviation emergency rescue system. These nodes are marked by ArcGIS, and the corresponding half-positive vector (Haversine) distances are calculated from the latitude and longitude coordinates of the nodes, which are approximately equal to the low-flying distance of the helicopters during the rescue.

In this case study, three S-76D helicopters take off from Longwan International Airport at the same time. It is assumed that the cruise speed of the helicopters is constant during the mission, and the helicopters hover at a certain altitude during each rescue hover. The crew is composed of two pilots, one paramedic, one winch operator, and one lifeguard. Based on the analysis of the scale of the mission and the existing configuration, the maximum number of trips per helicopter to complete the rescue mission is set to 4 to ensure that all disaster victims are rescued and to minimize crew fatigue, and the backup fuel coefficient is set to 0.1. The relevant parameters of the rescue helicopter are shown in Table 2.

The parameters of the rescue points include the settlement method and the number of disaster victims to be rescued. The case study takes into account the randomness and destructiveness of the disaster, some of the rescue points do not have landing and take-off conditions, so the helicopter can only hover for resettlement, while the level of injury and the corresponding number of disaster victims are randomly generated according to the characteristics of the model, and the parameters of the

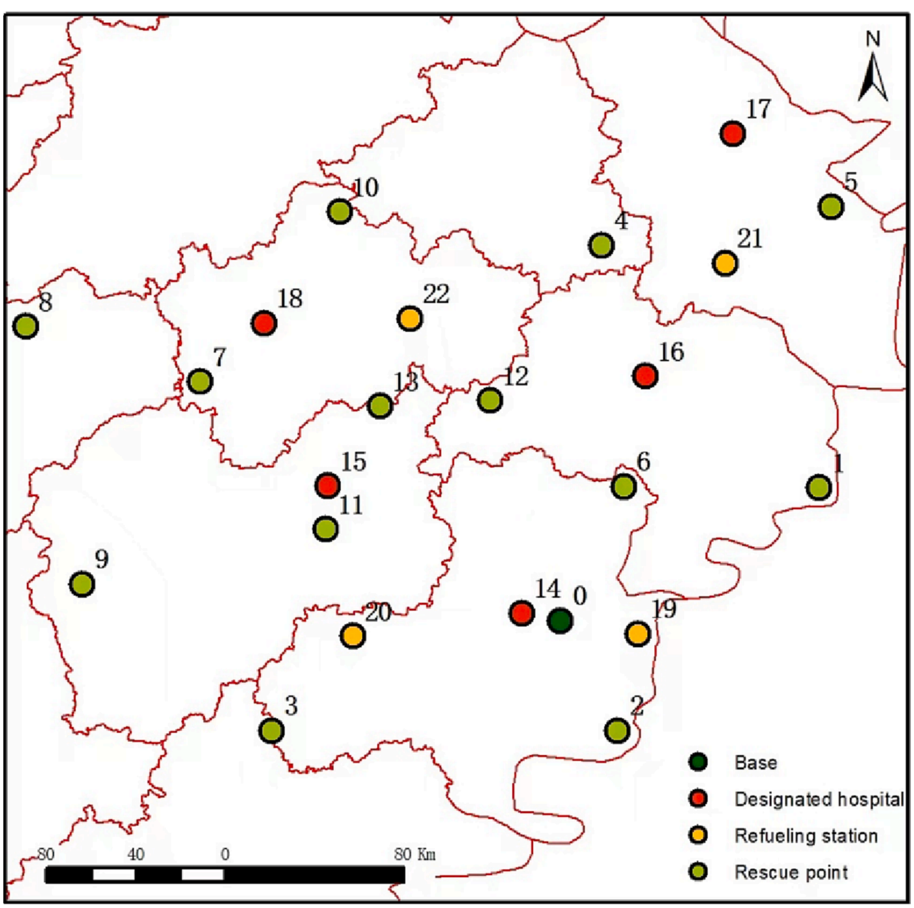

Fig. 6. Location of aviation emergency rescue mission nodes (marked by ArcGIS).

Table 2
Parameters of the helicopters for the rescue mission (get from S-76D flight manual).

Parameters	Value	Parameters	Value
Cruising speed	269 km/h	Oil capacity volume	1063L
Max number of passengers	2+12 seats	Cruise fuel consumption coefficient	350L/h
Number of crew members	5 people	Hovering fuel consumption coefficient	472L/h

rescue points are shown in Table 3.

Among the parameters related to disaster victims, the rescue time window for reaching the hospital for disaster victims with different injury levels is 1.5 h, 2 h, and 2.5 h respectively, and the unit disposal time for disaster victims with different injury levels in hover rescue is 0.13 h, 0.08 h, and 0.05 h respectively, and the rescue delay loss per unit time for disaster victims with different injury levels is $12, $8, and $3 respectively.

5.3. Results analysis

5.3.1. Computational result

The programming tool used to implement the algorithm is Python 3.9 and the computer processor configuration is 11th Gen Inter(R) Core (TM) i7-11700 T @1.40 GHz 1.39 GHz with 16.0 GB of RAM and the system type is Windows 10 64-bit operating system.

The parameters of the algorithm are set as follows: population size is 200, and the number of iterations is 300. The crossover probability is 0.9, where the preceding crossover probability is 0.9, the posterior crossover probability is 0.1, and the number of crossover cuts is 2. The mutation probability control parameter $P^1_{\max}$ is 0.1, and the control parameter changes to$P^2_{\max} = 0.9$ when the current optimal solution of the algorithm remains unchanged for 15 iterations. The mutation operations of 2-opt and insertion have a probability of 0.5, and the implementations based on backpacks and rescue points have the same probability. The number of iterative mutations is 2. When the iterative mutation result is worse, the parent result is retained with a probability of 0.8 and the worse child result is accepted with a probability of 0.2. M takes the value of 10000. The result of one iterative calculation is shown in Fig. 7.

From Fig. 7, in the beginning, the solution to the problem is randomly generated, and the objective function is relatively large. With the increase of the number of iterations, rescue delay loss of disaster victims gradually decrease under the genetic operation of the algorithm, and gradually converges after about 170 iterations. Finally, it is found that the loss of rescue delay is $253.48. The detailed route information of each emergency helicopter is shown in Table 4.

It can be seen from Table 4 that the two helicopters fly all four trips, while one helicopter only performs three trips of rescue missions, and the completion time of the entire rescue mission is about 4.1 h. Rescue points 13, 11, 3, 9, and 7 are split, but only the rescue mission at rescue point 13 is carried out by two different helicopters, all other rescue points are visited by the same helicopter at each point.

To further verify the stability of the algorithm's calculation results, this study conducts 20 calculations for the case, the initial population is generated randomly, and each iteration of the calculation starts from a different initial population. The calculation results are shown in Fig. 8. With a mean of $262.57 and a median of $252.60 for the 20 calculations, the data are relatively concentrated.

5.3.2. Comparative analysis

In this study, the maximum retained crossover and adaptive mutation genetic algorithm (MRC&AM-GA) has been developed to solve the model, also according to the characteristics of the problem, the 2-opt and insertion methods based on backpacks and rescue points have been designed in the mutation operation, and the multiple mutation execution logic has been developed. To further verify the effectiveness of the improvements to the algorithm, the computational results are compared with those of the standard genetic algorithm with crossover singleton generation and mutation fixed probability (CSG&MFP-GA).

Table 3
Parameters related to rescue points.

i	γ_i	c_i^r		
		$r = 1$	$r = 2$	$r = 3$
1	0	2	1	1
2	1	1	1	2
3	0	3	2	1
4	1	1	2	2
5	1	2	2	1
6	0	1	1	2
7	1	2	4	4
8	1	2	4	1
9	0	1	1	2
10	1	2	3	1
11	0	4	1	1
12	1	1	1	2
13	1	3	1	2

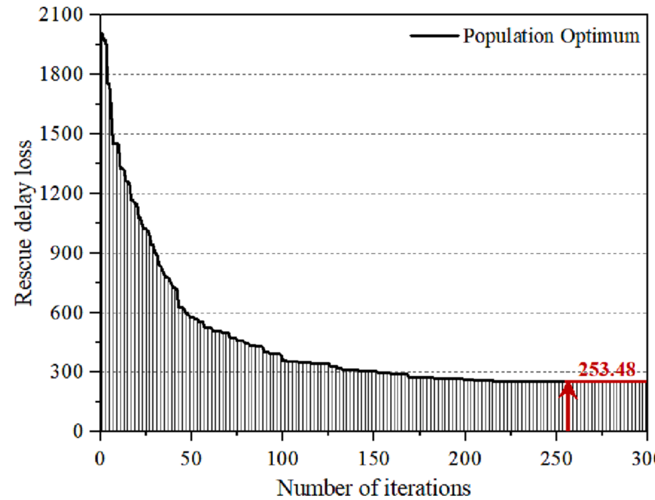

Fig. 7. The curve of fitness function changing with algorithm iteration.

Table 4
Information on the rescue routes of each emergency helicopter.

Crew number	Trip	Rescue route node access	Disaster victims loaded	Cumulative flight time
B-7327	1	$0 \to 13_{\{1,2\}} \to 11_{\{1,2\}} \to$ H2	9	59.62mins
	2	H2 $\to 10_{\{1,2,3\}} \to$ H2	6	120.03mins
	3	H2 $\to 11_{\{3\}} \to$ R2 $\to 8_{\{1,2,3\}} \to$ H5	8	225.85mins
B-7357	1	$0 \to 1_{\{1,2,3\}} \to 5_{\{1,2,3\}} \to$ H4	9	80.37mins
	2	H4 $\to 4_{\{1,2,3\}} \to$ H3	5	126.19mins
	3	H3 $\to 6_{\{1,2,3\}} \to$ R1 $\to 2_{\{1,2,3\}} \to$ H1	8	175.34mins
	4	H1 $\to 13_{\{3\}} \to$ H2	2	205.49mins
B-7359	1	$0 \to 3_{\{1,2\}} \to 9_{\{1,2\}} \to 7_{\{1\}} \to$ H5	9	87.09mins
	2	H5 $\to 7_{\{2,3\}} \to$ H5	8	132.25mins
	3	H5 $\to$ R4 $\to 12_{\{1,2,3\}} \to$ H2	4	191.09mins
	4	H2 $\to 3_{\{3\}} \to 9_{\{3\}} \to$ H5	3	245.66mins (max)

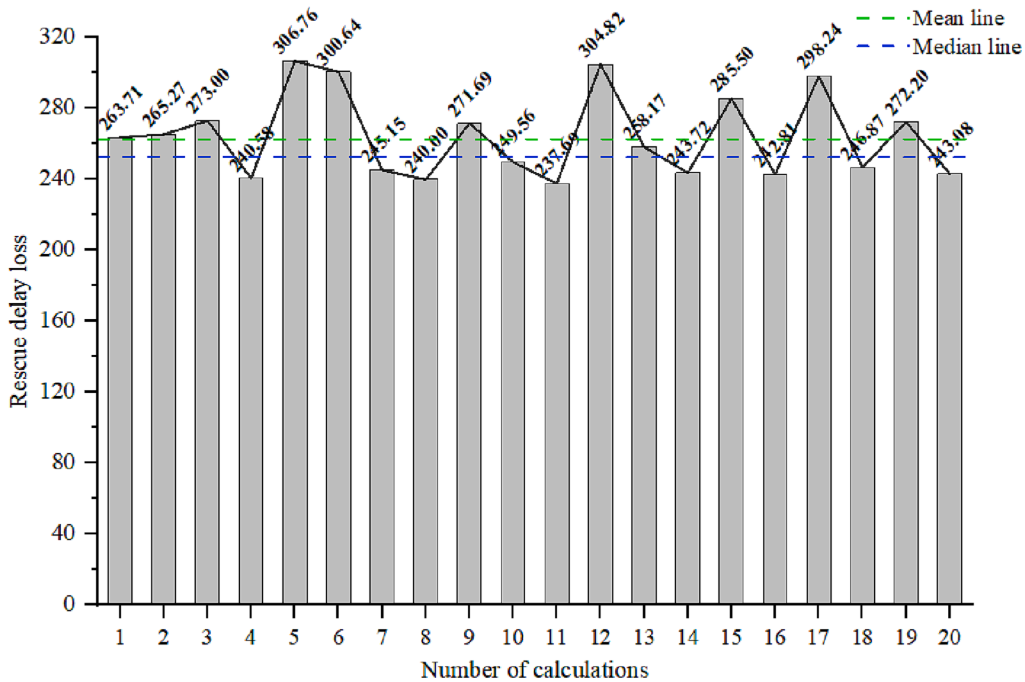

Fig. 8. Statistics of calculation results.

The iterative calculation process of the two algorithms is shown in Fig. 9.

The final outputs are $245.45 and $381.96 respectively. Both algorithms are calculated iteratively from the same initial population. It can be seen in Fig. 9, as the number of iterations increases, the objective function of MRC&AM-GA declines significantly faster than CSG&MFP-GA under the action of the maximum retained crossover method, proving that it has a stronger merit-seeking capability in the early stage. In the later stages of the algorithm's operation, the search tends to stagnate, and the adaptive rules strengthen the local search ability of MRC&AM-GA in the later stages, ensuring population diversity to a certain extent. To avoid the influence of accidental factors on the results of a single calculation, 10 calculations are performed for each algorithm, and the boxplot comparison of the two algorithms is shown in Fig. 10.

From a comparison of the 10 data sets, the MRC&AM-GA demonstrated stronger solution performance, with relatively small mean and median, as well as flatter boxe and less fluctuation in results.

5.3.3. *Sensitivity analysis*

In the aviation emergency rescue mission, the maximum number of loaded disaster victims and backup fuel of the helicopter can change the

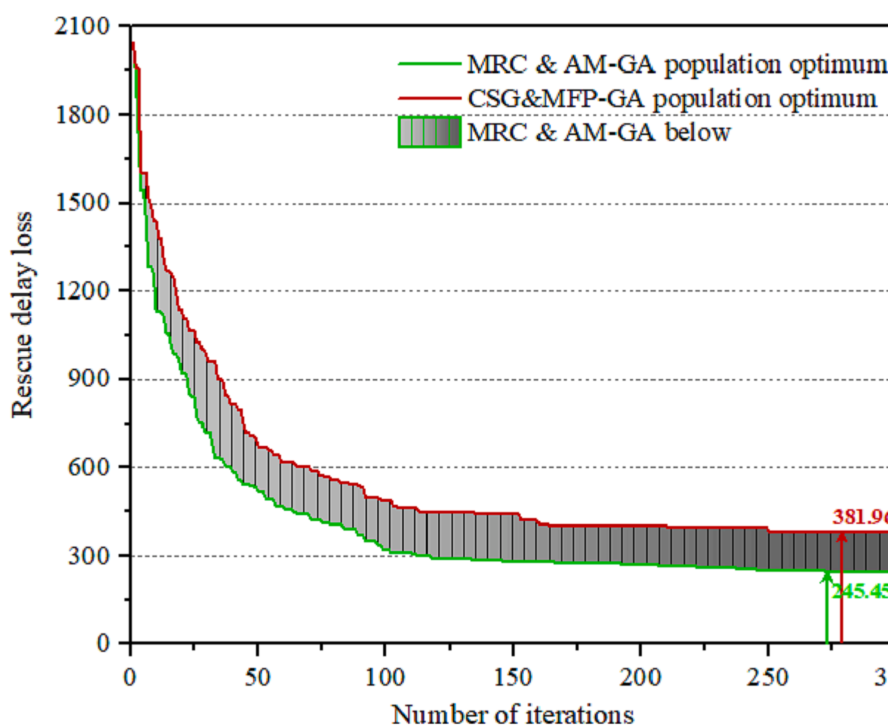

Fig. 9. The fitness curve of the two algorithms.

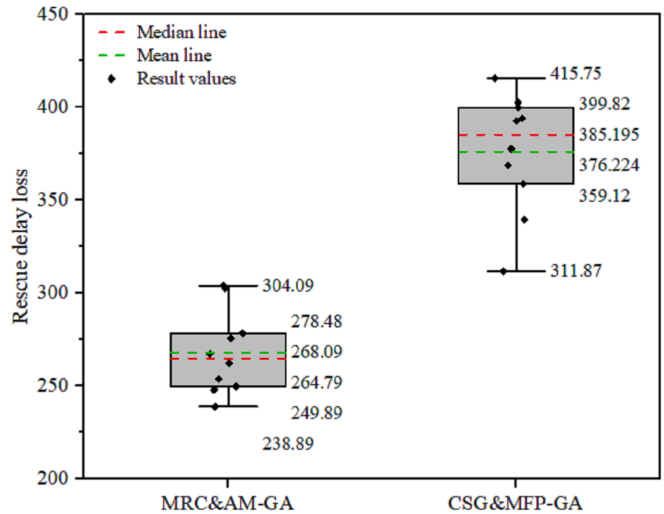

Fig. 10. Comparison of two algorithm boxplots.

order of access nodes on the route, thus affecting the rescue time. In this study, while keeping other conditions unchanged, the algorithm is calculated from the same initial population. The sensitivity analysis of these two factors is carried out respectively and the results are shown in Fig. 11.

1) Sensitivity analysis of the maximum number of disaster victims loaded

In the case of this study, the S-76D helicopter used for rescue mission has 2+12 seats, and there are 5 crew members including medical staff. Professional medical rescue helicopters are equipped with simple medical equipment, such as ventilators. During a normal rescue mission, medical personnel accompany the helicopter to provide medical cover, additional medical staff may be on board if necessary. However, in special demand situations, due to space constraints in the cabin, it is possible to reduce the number of medical staff or overload the helicopter as appropriate, while ensuring its safety. Therefore, to further investigate the effect of the number of disaster victims on board the helicopter on the results, the variation of the objective function is calculated for the cases of accommodating 7 to 12 people respectively.

From Fig. 11(a), it can be concluded that the number of disaster victims loaded on the helicopter has an impact on the rescue delay losses. The overall trend is that the lower the number of disaster victims loaded, the greater the rescue delay loss. The objective function amounts to $343.32 with the addition of two medical staff. The difference in rescue delay losses is not significant when the crew members are 4,5 and 6. The downward trend in the objective function accelerates when the helicopter is overloaded by one to two people. Therefore, if necessary, a suitable overload solution can be selected while meeting the maximum take-off weight and safety of the helicopter.

2) Sensitivity analysis of helicopter safety backup fuel

Although the fuel consumption parameters for helicopter cruising and hovering are known in this paper, there is still a risk of increased fuel consumption due to unforeseen circumstances during rescue mission, and backup fuel ensures the safety of the helicopter in the air to a certain extent. Subjectively, the increase in backup fuel can shorten the range of the helicopter and increases the frequency of fuel supply, thus extending the rescue time. In this study, the change of rescue delay loss is calculated separately for different coefficients.

As can be seen in Fig. 11(b), there is no significant change in the objective function when the backup fuel coefficient is less than 0.20, all three helicopters refuel once, when it is not wise and safe to keep too little backup fuel. At a coefficient equal to 0.15, it is approximately the international standard for 30-minute cruise flight reserve fuel. In case it is greater than 0.20, the rescue delay loss increases obviously, and the shortening of the maximum range of the helicopter directly leads to an increase in the number of visits to refueling stations, which affects rescue time. Therefore, the decision-maker should set the backup fuel reasonably according to helicopter safety.

6. Conclusions and discussions

This study is based on an emergency mission scenario, in which disaster victims waiting to be rescued are discrete split according to their degree of injury, and given different urgency rescue time windows. The model also takes into account the characteristics of helicopter performance, and establishes an air emergency rescue route planning problem that considers the split of disaster victims according to backpacks, with the loss of rescue delays as the decision objective. A genetic algorithm is used to solve the model based on a virtual rescue point coding approach to provide a scientific route plan for emergency decision-makers.

Several conclusions can be drawn from the problem characteristics and the analysis of the results: (1) the model can effectively address the differentiated characteristics of the individual demands of rescue targets; (2) the designed genetic algorithm solution is relatively stable and can provide a more satisfactory solution; (3) some of the parameters of the helicopter can affect the quality of rescue mission completion, and decision-makers should make reasonable adjustments according to the actual needs.

In a related study by other scholars, Tirkolaee et al. (2019a)

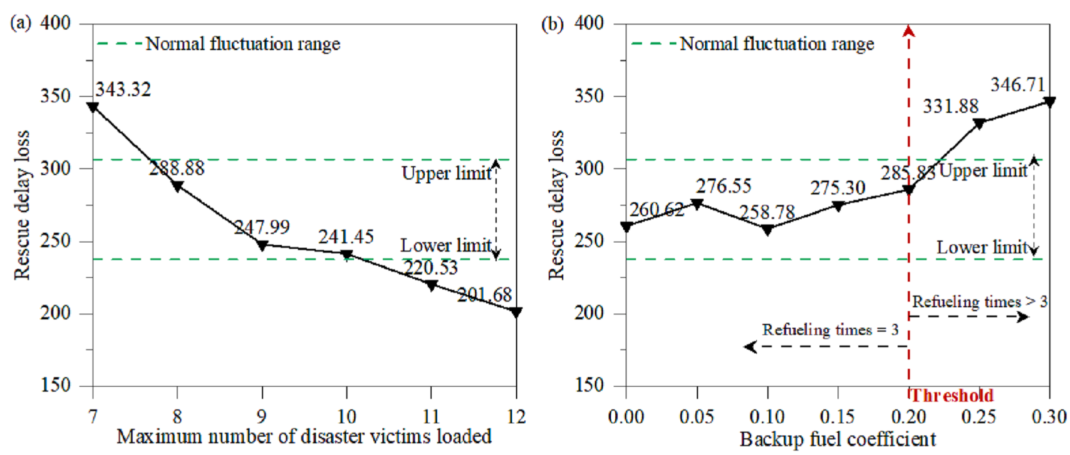

Fig. 11. Sensitivity analysis of maximum number of disaster victims loaded and backup fuel.

investigated the multi-trip vehicle routing problem with time windows of particular relevance to municipal waste collection, considering multiple vehicle trips and time windows as the most critical features of the problem. Still using municipal waste collection as a research context. Tirkolaee et al. (2019b) extended their previous research to the case of demand uncertainty and constructs a bi-objective robust model. Khalilpourazari and Doulabi (2022) studied the problem of designing blood supply chain networks in emergency, and the parameters of the proposed mathematical formulation are also uncertain. For the treatment of uncertainty, robust optimization models were constructed in the papers (Ozmen, Kropat, & Weber, 2017; Özmen, Weber, Batmaz, & Kropat, 2011) based on polyhedral uncertainty sets. These discussions of uncertainty and how to deal with it inspire for our future work.

Compared to the mentioned scholars' research, we consider more complex real-life problem scenarios, not only considering multiple trips and time windows, but also considering the characteristics of demand variability, which leads to the model innovation of this study. However, in contrast to their research, the parameters in our model are all deterministic, and there is much scope for expansion in terms of parameter uncertainty for emergency scenarios, particularly the impact of environmental factors on helicopter performance and the uncertainty of rescue demands. Improving the applicability of the model is a challenge we will need to face in the future.

CRediT authorship contribution statement

Yi Li: Methodology, Software, Investigation, Visualization, Writing – original draft. **Guoqing Zha:** Resources, Data curation. **Xing Pan:** Conceptualization, Supervision, Project administration. **Yiyong Xiao:** Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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