A two-Stage UAV Routing Problem with Time Window Considering Rescheduling with Random Delivery Reliability

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Abstract

Reliability is an important metric for unmanned aerial vehicles (UAVs) to perform important, complex, and dangerous tasks. In addition, reliability influences the operational cost in UAVs routing. In order to reduce the operational cost of UAVs tasks, a method of routing strategy optimization is proposed from a view of mission reliability in this paper to address the limitations in routing scheduling. Different from previous studies on the UAVs routing optimization problem, this paper proposes a method that can reduce the operational costs of UAVs tasks based on the mission reliability. This method includes two stages: the pre-optimization stage and the rescheduling stage. In the pre-optimization stage, an optimal UAVs route solution is obtained for all the targets, while in the rescheduling stage, new UAVs are dispatched to the unvisited targets in the pre-optimization stage based on the new optimal UAVs route.

Keyword Unmanned aerial vehicle, System reliability, Vehicle routing optimization, Rescheduling strategy, Variable neighborhood search

1 Introduction

The routing optimisation problem of unmanned aerial vehicles (UAVs) in the military environment, one of the vehicle routing problems (VRP) in real life, has been a research hotspot in the field of combinatorial optimisation and operational research [1,2,3]. Specifically, in the field of military operations, UAVs are often dispatched to perform important and dangerous tasks, such as carrying valuable resources and expensive materials. However, UAVs are attacked by shocks, such as enemy shooting, electromagnetic pulse, extreme weather, and so on, which will not only destroy UAVs and expensive materials within them, but also lead to mission failures. Therefore, it is necessary to study the reliability of the UAVs routing optimisation problem, in order to extend the application field of UAVs.

The UAVs routing problem is complicated especially when they have to visit dangerous targets [4,5,6]. Many scholars have researched the problem of UAVs routing optimisation problems, such as Kinney et al. [7], Obelin et al. [8], and Coelho et al. [9]. In a study from Shima et al. [10], a problem of cooperative multitasking distribution was proposed and the computational complexity was analysed. Since it is an NP-hard problem, Boulares et al. [11] applied Recursive Area Clustering algorithm to further improve the efficiency in solving this kind of problem. Tian et.al. [12] planned the optimal route by improving the A* (A-star) and gravitational search algorithm, in which the A* algorithm is the most effective and direct method to find the shortest route in the static road network. An algorithm of adaptive selection mutation constraining differential evolution was proposed by Yu et al. [13], which plays an important role in disaster relief. In the study of Qu et al. [14], HSGWO-MSOS, combining simplified grey wolf optimizer (SGWO) and modified symbiotic organisms search (MSOS), was studied and efficiency was tested by the simulation results. Ye et al. [15] applied an adaptive genetic algorithm (AGA) with the assumption of the heterogeneity and task coupling constraints of UAVs. However, these studies did not consider the situation that the UAVs could return to the base before finishing the tasks.

In the research of Peng [16], the aborting strategy of UAVs was taken into consideration after being attacked by shocks. External shocks and internal failure are considered in the aborting strategy in the study of Qiu [17, 18], in which the author divided the failure process of the system into two parts: one is from new defects to initial defects, and the other is from new defects to the failure. Based on the study, mission reliability and system survivability were derived. Yang [19] considered the situation that possible imminent fatal failure may happen during the task, so he introduced information warning signals to abort the strategy. These papers have taken aborting strategies into consideration, but they ignore those unvisited targets.

Inspired by previous studies, this paper proposes a three-step variable neighbourhood scatter search algorithm to solve the problem of UAVs routing optimisation with a background for capacitated vehicle routing problem with stochastic demand (CVRPSD) [20]. In CVRPSD, the demand of customers is random. When the given route is not served by the distribution vehicle according to the order of customer points, the route must be re-planned. CVRPSD vehicle routing optimisation has two stages including pre-optimisation stage and rescheduling stage, which can also be applied to the UAVs routing optimisation problem. The shocks by which the UAVs are attacked during the flight are random as well. In the pre-optimisation stage, an optimal initial route assignment scheme is generated. And then, a failure point with a high probability of UAVs being destroyed will be provided through simulation. Therefore, during the flight, if the probability of UAVs being destroyed is higher than a certain level, the aborting strategy will be adopted which means UAVs have to return to the base before the failure point. In addition, this paper assumes that the UAVs will not be destroyed on the way back to the base because UAVs have no mission at that time and the probability of destruction can be greatly lower than before. The targets after the failure point are regarded as the unvisited targets. In the rescheduling stage, new UAVs will be rescheduled to visit the unvisited targets.

There are two aspects of reliability that can increase the cost of the mission. First, there are some targets that are not visited by UAVs due to routing strategy, since UAVs will stop their flight and back to base according to the degree of self-damage. Obviously, unvisited targets will incur some losses in terms of the mission. Second, the destruction of UAVs will also incur losses because of the UAVs cost. In this case, optimizing the UAVs routing is an effective way to reduce the total cost of the mission. If the routing strategy tries to avoid shocks, the probability of UAVs being destroyed will be reduced, but the number of unvisited targets will be increased. In this case, there is an issue about how to make routing policy. If the UAV backs in advance, the cost of UAVs is decreased with the probability of UAVs destruction, but the cost of mission failure is increased with the number of unvisited targets. Thus, in order to achieve global optimum, the objective of this study is to minimize the total cost considering the mission reliability.

Therefore, to reduce the total costs of the mission, this paper proposes a model to evaluate the mission reliability. The model includes two stages: the pre-optimisation stage and the rescheduling stage. A three-step algorithm is proposed to optimize the routing strategy of UAVs. The rest of this paper is arranged as follows. Section 2 describes the study problem and proposes some assumptions. Section 3 presents the model of reliability evaluation. Section 4 gives a optimization strategy to search the optimal result. Section 5 shows a numerical example. Section 6 concludes this study.

2 Problem description

First of all, it is needed to declare the reliability concept used in this study. The reliability considered in this study is mainly based on mission reliability which means the probability of mission success without being destructed. Basically, higher reliability needs higher cost. In this case, this study can balance them by optimizing the scheduling and rescheduling of UAVs routing. For example, the optimal strategy can be obtained to minimize the cost to meet a requirement of reliability, or to maximize the reliability under a constraint of cost. In details, the high reliability is indicated by the low probability of UAVs destruction and few unvisited targets according to the system reliability definition in many complex processes or missions [21-29]. The reliability is defined by two metrics: the probability of UAVs being destroyed and the number of unvisited targets; and both of them are negatively related with reliability. Therefore, so as to increase the reliability of the mission, the probability of UAVs destruction and the number of unvisited targets should be decreased, which means the total cost should be minimized in routing optimization problem.

For UAVs operation, UAVs depart from the base and then visit the assigned targets on the optimal route. During the flight, UAVs are randomly attacked by shocks (enemy shooting, electromagnetic pulse, extreme weather, etc.), which brings the risk of being destroyed. The costs can be estimated in two potential parts. If UAVs are destroyed during the flight, the costs include the costs of UAVs and other values like materials they carry, time-cost and so on. If UAVs cannot finish the missions because of the destruction or flying back to the base in advance, the costs also include the costs for the unvisited targets. For example, when a target that is in urgent need of medicine is not visited by UAVs, there will be many casualties which are seen as the costs of that target. Moreover, some targets may be in long distance which cost a lot if visited so that UAVs will not choose to visit it as well. It should be noted that the two parts of cost may occur simultaneously under a condition where the UAV is destroyed and some targets are unvisited, but the two parts of cost are calculated separately. The costs of unvisited targets are difficult to measure in practice. Therefore, this paper refers to the mechanistic mathematical framework of Gomez *et al.* [30] which is based on the economic evaluations and the actual situation to present the costs parameters directly.

Inspired by CVRPSD, the situation in this paper is described as two stages: the pre-optimization stage and the rescheduling stage. In the pre-optimization stage, UAVs visit the targets based on the optimal route and then return to the base before the failure point. Failure point is the target position where the UAV has a great probability to be destroyed if it visits this target since the UAV has suffered too many shocks to keep flying when it arrives there. Generally, the failure point is known by the ground commanders of UAVs in advance. In this study, the failure point is obtained through simulation.

In the rescheduling stage, new UAVs will be rescheduled to visit the unvisited targets in the pre-optimization stage according to a new optimal route. In this stage, UAVs still may be attacked by shocks and have the probability of destruction which can cause some targets unvisited. An example is showed in Fig. 1. In the pre-optimization stage, UAVs have to visit five target points (points 1 to 5). The optimal route is that UAVs depart from the base (point 0) and then visit the points from 1 to 5 in order.

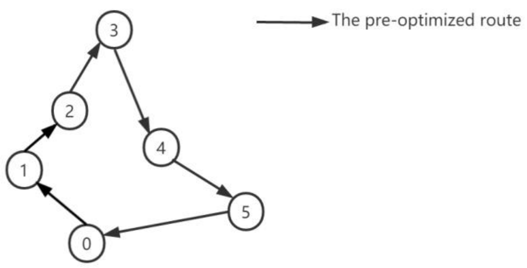

Fig. 1 The optimal route in pre-optimisation stage

During the flight, the UAVs are attacked by shocks which will incur huge costs. Therefore, the aborting strategy and failure point are introduced to reduce the probability of the UAVs being destroyed and minimize the total costs of UAVs' tasks. A failure point, which means that UAVs will be destroyed at this point, is provided through simulation. UAVs have to return to the base before the failure point. In addition, this paper regards all the targets which are not visited by UAVs as the unvisited targets. In Fig. 2, if point 3 is the failure point, UAVs have to return to point 0 (the base) after visiting point 2. The unvisited points are points 3, 4 and 5. If the UAV is destroyed between point 1 and point 2, the unvisited points include points 2, 3, 4 and 5. In this stage, the cost of UAV destruction is calculated and the cost of unvisited targets is not considered because those unvisited targets will be reassigned in the next stage.

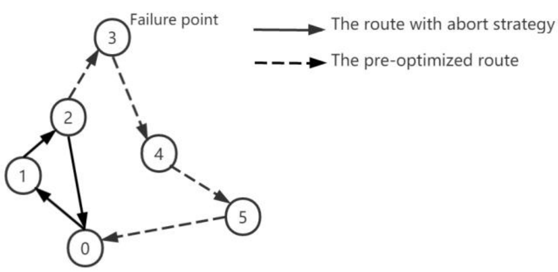

Fig. 2 The failure point and the abort strategy

Next, in the rescheduling stage, new UAVs are rescheduled to visit the unvisited targets based on a new optimal route. In Fig.3, the optimal route in the rescheduling stage is that the UAVs depart from point 0 and then visit points 5, 4 and 3 in order and return to point 0 at last. In this stage, the cost of UAV destruction and the cost of unvisited targets are both considered, i.e., the cost of UAV destruction plus the cost of unvisited targets equals the total cost.

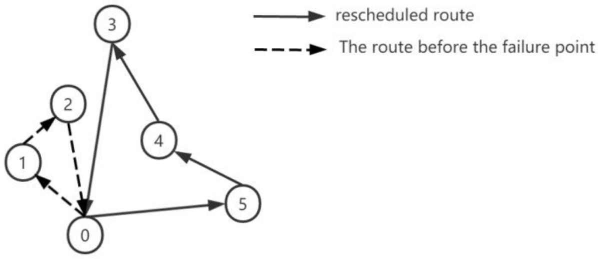

Fig. 3 The rescheduled route of unvisited targets in rescheduling stage

Generally speaking, this paper assumes that there are N targets that need to be visited, and all the targets are named as $V=\{0,1,2,3,\cdots,n,\cdots,N\}$, where 0 represents the base and n represents the target n. There are M UAVs available which are indicated in a set $F=\{1,2,3,\cdots,f,\cdots,M\}$. The frequency at which a UAV is attacked by shocks is assumed to be a constant p, which is consistent with the uniform Poisson process. The probability of a UAV being attacked by l shocks and lastly being destroyed is expressed as $C(l)$. The destruction costs of one UAV are expressed as c_u. And the costs of one unvisited target is expressed as c_t.

In this model, the undirected graph $G(V,A)$ is used to show targets and the base, where the edge set is $A=\{(i,j):i\neq j,i,j\in V\}$, (i,j) indicates the distance from the i th target to the j th target. The time of travel $t(i,j)$ is required. Each UAV can only arrive the i th target and finish its visit in the time window $(e(i),l(i))$, in which the lower limit of the time window is $e(i)$ and the upper limit of the time window is $l(i)$. The visiting time is $s(i)$ and the end time of visit for the i th target assigned to UAV f is denoted as $T(f,i)$. The set of targets assigned to the UAV f is represented by H_f, and the number of targets allocated is $|H_f|$. The i th target in the route assigned to the UAV f is denoted as $H_f(i)$. The number of shocks between the target i and the target j during the flight of UAV f is described as $l_f(i,j)$.

Then accodring to the studied problem, some assumptions are proposed as below

(1) All the UAVs for tasks are of the same type, and the parameters of each UAV are fixed, such as flight speed, flight range, and so on;

(2) Each target only need to be visited once by UAVs in the mission;

(3) The shocks to each UAV follow an independent and identical Poisson process during the whole mission;

(4) UAV can only be destructed by shocks and the destruction probability is related to the number of times of shocks;

(5) Internal faults are not considered since their frequency is negligible compared with shocks in the

mission;

(6) Total mission costs include the costs of UAVs destruction and the costs of unvisited targets;

(7) Each target can be reassigned but only once;

(8) The UAVs are safe on the way back to the base;

(9) The cost of keeping the time windows available when rescheduling is not considered because the model is more suitable for routine mission whose time windows open regularly and UAVs set out to the missions regularly. (Routine mission pay more attention on the total cost of the mission.)

(10) The UAVs can keep flying and visiting the targets unless it is destroyed.

3 Reliability measures evaluation

3.1 The end time of visit to each target

Each UAV visits the targets based on the optimal route. In order to simplify this problem, the upper limit of the time window is not considered when describing the end time of visit to each target, which will be considered in section 3.5. The end time of visit to the i th target which is assigned to UAV f is described as $T(f,i)=\max(e(H_f(i)),T(f,i-1)+t(H_f(i-1),H_f(i))+s(H_f(i)))$. The total traveling time of UAV f without being aborted or destroyed is $T(f,|H_f|)+t(H_f(|H_f|),0)$.

3.2 The probability of UAVS successfully returning to the base

Assuming that the UAV f is not destroyed during the traveling, visits all the targets assigned and then safely return to the base, the probability of UAV f successfully returning to the base is

$$P_S(f)=\sum_{l=0}^{\infty}\frac{\exp\{-p\cdot(T(f,|H_f|))\}(p\cdot(T(f,|H_f|)))^l}{l!}(1-C(l)) \tag{1}$$

where $\frac{\exp\{-p\cdot(T(f,|H_f|))\}(p\cdot(T(f,|H_f|)))^l}{l!}$ means the probability that UAV f is attacked by l shocks in total after visiting all the targets assigned. And $1-C(l)$ is the probability that the UAV f is not destroyed after being attacked by l shocks.

3.3 The expected number of unvisited targets for each UAV

During the whole travel, the destruction of UAVs causes the failure of mission and leaves some targets unvisited which will increase the number of unvisited targets. The more the probability of UAVs destruction, the more the number of unvisited targets will be.

The probability of UAV f being destroyed before finishing visiting the first target assigned is

$$P_0(f)=\sum_{l=0}^{\infty}\frac{\exp\{-p\cdot T(f,1)\}(p\cdot T(f,1))^l}{l!}C(l) \tag{2}$$

where $\frac{\exp\{-p\cdot T(f,1)\}(p\cdot T(f,1))^l}{l!}$ is the probability that UAV f is attacked by l shocks in total after visiting the first target.

The probability of UAV f being destroyed after visiting i th targets $\left(i\in\left(0,\left|H_f\right|-1\right)\right)$ is

$$\begin{aligned}P_i(f)=&\sum_{l=0}^{\infty}\frac{\exp\{-p\cdot T(f,i)\}(p\cdot T(f,i))^l}{l!}\\&\sum_{m=0}^{\infty}\frac{\exp\{-p\cdot(T(f,i+1)-T(f,i))\}(p\cdot(T(f,i+1)-T(f,i)))^q}{q!}\\&(C(l+q)-C(l))\end{aligned} \tag{3}$$

where $\frac{\exp\{-p\cdot(T(f,i+1)-T(f,i))\}(p\cdot(T(f,i+1)-T(f,i)))^q}{q!}$ is the probability that UAV f is attacked by q shocks between the i th target assigned and the $(i+1)$ th target assigned, while $(C(l+q)-C(l))$ represents the probability that UAV f is not destroyed after being attacked by the l shocks to the q shocks.

The expected number of unvisited targets for each UAV is $\sum_{i=0}^{\left|H_f\right|-1}P_i(f)\left(\left|H_f\right|-i\right)$. (4)

3.4 A special case for performance measures evaluation

This paper uses a simple example which is shown in Fig. 4 to explain the evaluation of performance measurement. Supposing m=2 and N=4, target 1 and target 2 are visited by UAV 1 and target 3 and target 4 are visited by UAV 2. Therefore, $H_1=\{1,2\}$ and $H_2=\{3,4\}$ are got. As shown in Fig. 4, the solid line indicates the optimal route of UAV 1 and the dotted line indicates the optimal route of UAV 2.

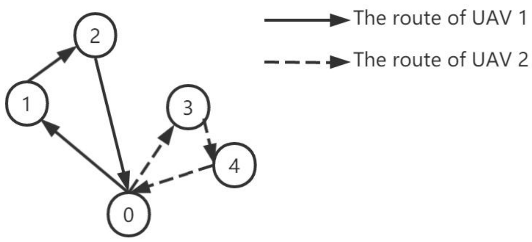

Fig. 4 A special example

On the basis of section 3.1, the end time of visit to target 1 is denoted as

$T(1,1)=\max(e(1),t(0,1))+s(1)$ and the end time of visit to target 2 is denoted as $T(1,2)=\max(e(2),T(1,1)+t(1,2))+s(2)$. The traveling time in a total of UAV 1 without the consideration of UAVs destruction is $T(1,2)+t(2,0)$. Furthermore, on the basis of the formula (1), the probability that the UAV finishes the visit of two targets and successfully return to the base is

$$P_S(1)=\sum_{l=0}^{\infty}\frac{\exp\{-p\cdot(T(1,2))\}(p\cdot(T(1,2)))^l}{l!}(1-C(l)) \tag{5}$$

The probability of UAV 1 being destroyed before finishing the visit to the first target is

$$P_0(1)=\sum_{l=0}^{\infty}\frac{\exp\{-p\cdot T(1,1)\}(p\cdot T(1,1))^l}{l!}C(l) \tag{6}$$

The probability of UAV 1 being destroyed after finishing the visit to the first targets is

$$\begin{aligned}P_1(1)=\sum_{l=0}^{\infty}&\frac{\exp\{-p\cdot T(1,1)\}(p\cdot T(1,1))^l}{l!}\\&\sum_{m=0}^{\infty}\frac{\exp\{-p\cdot(T(1,2)-T(1,1))\}(p\cdot(T(1,2)-T(1,1)))^q}{q!}\\&(C(l+q)-C(l))\end{aligned} \tag{7}$$

The expected number of unvisited targets for UAV 1 is $2P_0(1)+P_1(1)$. (8)

3.5 The optimal routing optimisation strategy

In this model, the random chance constraint is introduced to test whether the UAV f keeps on visiting the targets assigned. Firstly, the pre-set risk preference value α is given. At that time, the relationship between the number of shocks $l_f(i,j)$ which UAVs will be attacked from i th target to j th target and the pre-set threshold Q is stochastic constraint. It is hoped that the random constraint will hold at the pre-set preference value level α, which means the chance constraint $\Pr\left\{\sum_{k=0}^{|H_f|-1} l_f(H_f(k),H_f(k+1))\le Q\right\}\ge\alpha$ based on the random probability measure.

Moreover, this model only considers the costs of UAVs destruction and the costs of unvisited targets. And the optimal routing strategy needs to reduce the total costs of UAVs tasks. The optimal route can be described as

$$\{H_1,\cdots,H_m\}=\arg\min\left\{\sum_{f=1}^{m}\left(c_u(1-P_s(f))+c_t\sum_{i=0}^{|H_f|-1}P_i(f)(|H_f|-i)1(H_f>0)\right)\right\} \tag{9}$$

Subject to:

$$m=1,2,3,\cdots,M\quad m\le M \tag{10}$$

$$|H_f|=0,\cdots,N\text{, for any }f=1,\cdots,m \tag{11}$$

$$H_f(i)=1,\cdots,N \text{, for any } f=1,\cdots,m \text{ and } i=1,\cdots,|H_f| \tag{12}$$

$$(H_f(i)-H_k(d))^2>0.5 \text{, for any } (f-k)^2>0.5 \text{ or } (i-d)^2>0.5 \tag{13}$$

$$T(f,i)\leq 1(H_f(i)) \text{, for any } i=1,\cdots,|H_f| \text{ and } f=1,\cdots,m \tag{14}$$

$$\Pr\left\{\sum_{k=0}^{|H_f|-1} l_f(H_f(k),H_f(k+1))\leq Q\right\}\geq\alpha \text{ , for any } |H_f(0)|=0 \text{ and } f=1,\cdots,m \tag{15}$$

Eq. (10) indicates that there is a surplus of UAVs. Eq. (11) indicates that the number of targets assigned to each UAV is no more than N. Eq. (12) indicates that the valid targets should be mapped by all the elements of H_f. Eq. (13) indicates that each target is only assigned to one UAV, and only visited by one UAV once. Eq. (14) indicates that each visit should be completed within the time window of each target. Eq. (15) is a random shock chance constraint to ensure that the total number of shocks on UAVs does not exceed Q which is greater than the pre-set confidence level.

3.6 Equivalent formation of stochastic chance constraint

In the model, the stochastic chance constraint is transformed into the equivalent form of deterministic type for easy calculation. For the UAV f, the shock $l_f(i,j)(i,j\in V\ f\in F)$ is independent and identically distributed random variables. According to the central limit theorem, the total shocks follow the normal distribution approximately, and there is expectation $M_f=\sum_{i,j\in V}E[l_f(i,j)]$, where $E[l_f(i,j)]=P(l_f(i,j))\cdot l_f(i,j)$ and $P(l_f(i,j))=\dfrac{\exp\{-p\cdot(T(f,j)-T(f,i))\}(p\cdot(T(f,j)-T(f,i)))^{l_f(i,j)}}{l_f(i,j)!}$, as well as the standard deviation [31] is

$$S_f=\left(\sum_{i,j\in V}\mathrm{var}[l_f(i,j)]\right)^{\frac{1}{2}}=\sqrt{M_f} \tag{16}$$

When the constant $z_{1-\alpha}$ satisfies $z_{1-\alpha}=\phi^{-1}(\alpha)$, Eq. (15) is equivalent to

$$\Pr\left\{\frac{\left(\sum_{i,j\in V}l_f(i,j)-M_f\right)}{S_f}\leq z_{1-\alpha}\right\}=\alpha, f\in F \tag{17}$$

Furthermore, the equivalent deterministic constraint is [32]:

$$M_f+z_{1-\alpha}\cdot S_f\leq Q, f\in F \tag{18}$$

The extended form is:

$$\sum_{i,j\in V} E\left[l_f(i,j)\right] + z_{1-\alpha}\cdot\left(\sum_{i,j\in V}\operatorname{var}\left[l_f(i,j)\right]\right)^{\frac{1}{2}} \le Q, f\in F \tag{19}$$

Since the frequency of shocks follows Poisson distribution and the expected value and variance are equal, there exists a constant $\overline{Q}$ such that Eq. (15) is:

$$\sum_{i,j\in V} E\left[l_f(i,j)\right] \le \overline{Q} \tag{20}$$

$$\overline{Q} = \frac{1}{2}\left(2Q + {z_{1-\alpha}}^2 - \sqrt{{z_{1-\alpha}}^4 + 4Q\cdot {z_{1-\alpha}}^2}\right) \tag{21}$$

4 optimisation strategy: Three-step variable neighbourhood scatter search

In order to optimize the routing problem of UAVs, a three-step variable neighbourhood scatter search (VNSS) algorithm is proposed. The first step is to calculate the pre-optimal routes. In this step, this paper uses the central limit theorem to calculate the destruction probability of UAVs, and uses the chance constraint model to optimize the routes of UAVs to find the scheme with the minimum objective function [33]. The second step is to find the failure points in which failure points are obtained through simulation to remind the UAVs to return to the base before their destruction. The third step is to find the rescheduling optimal routes. As the probability of UAVs being destroyed is random [34,35], there will be some unvisited targets. Therefore, a new optimal route will be rescheduled for UAVs so as to visit the unvisited targets.

4.1 Algorithm framework

VNSS is an integration of variable neighbourhood search (VNS) and scatter search (SS). As an improved local search algorithm [36], VNS takes advantage of the neighbourhood structure and works more effectively on both concentration and evacuation. Based on a population-based global search strategy, SS obtains optimal and diverse solutions. And then it finds the global optimal solution by merging subsets and updating reference sets.

The algorithm framework includes three steps which are as follows:

Step 1. Calculating the optimal solution in the pre-optimization stage;

Step 2. Calculating the failure points in the pre-optimization stage;

Step 3. Calculating the optimal route in the rescheduling stage.

The basic flow of the variable neighborhood scatter search algorithm is shown below in Fig.5. And the Pseudo code of the algorithm is shown below in Table 1.

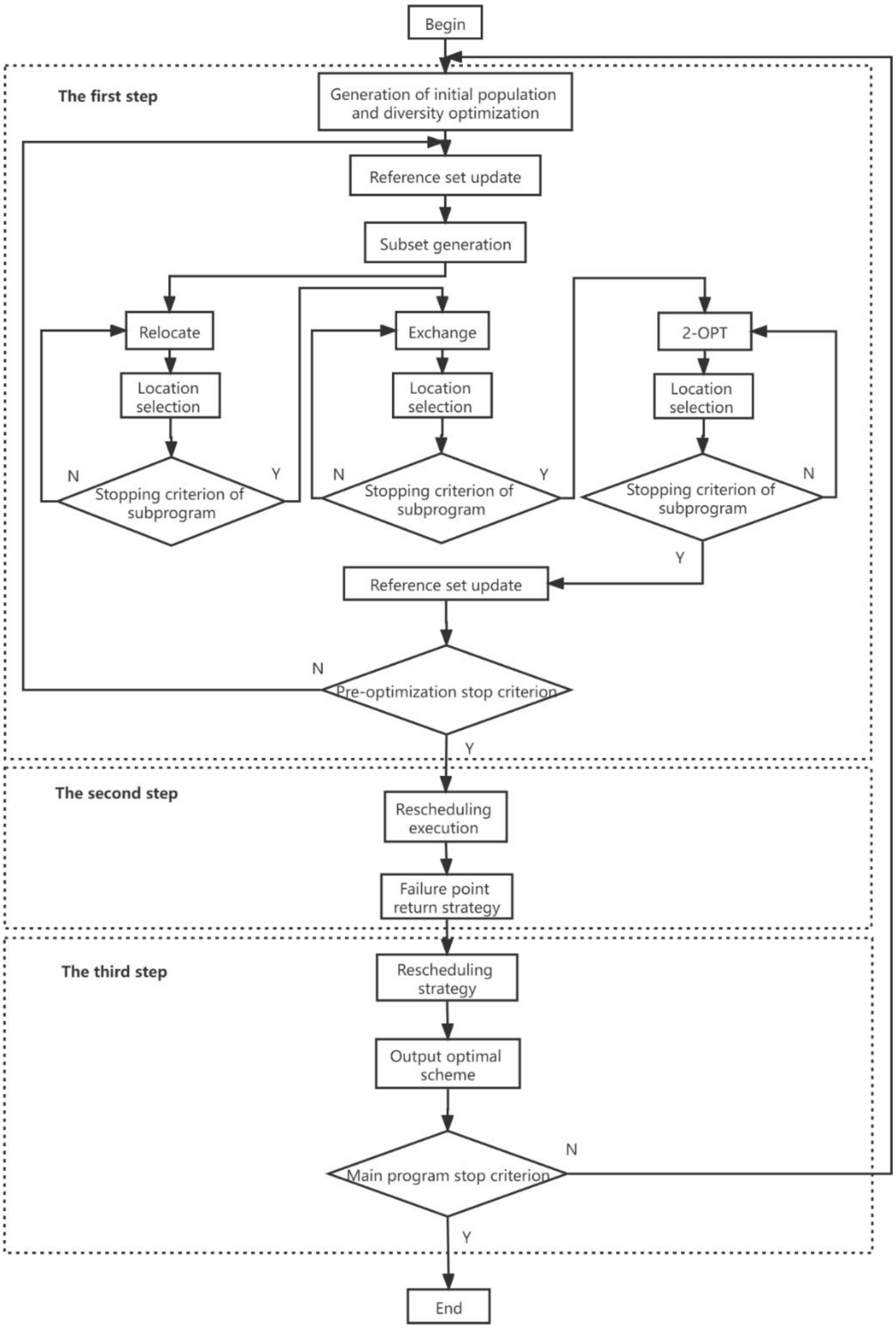

Fig. 5 The basic flow of variable neighbourhood scatter search

Table 1 The Pseudo code of the algorithm

Step 1 Calculating the optimal solution in the pre-optimization stage	
1	f_i←0, f ←the number of UAVs available
2	While main program stop criterion == false

If $f_i > f$
break
End if
Repeat
IS_i ←generation of initial population and diversity optimization
RS_i ←Reference set undated
SS_i ←Subset generation
Repeat
Relocate: delete the i point and insert it into the new location
Location selection: S_i ←select low costs scheme
Until stopping criterion of subprogram == true
Repeat
Exchange: Swap the positions of point i and point j
Location selection: S_i ← select low costs scheme
Until stopping criterion of subprogram == true
Repeat
2-OPT: Swap parts of route i and route j
Location selection: S_i ← select low costs scheme
Until stopping criterion of subprogram == true
$IS_{i+1} \leftarrow S_i$
$i \leftarrow i+1$
$f_i \leftarrow f_i + 1$

25	Until pre-optimization stop criterion == true
Step 2 Calculating the failure points in the pre-optimization stage	
1	$F_P = \{1,2,\cdots, p\}$←failure points return strategy through simulation
Step 3 Calculating the optimal route in the rescheduling stage	
1	$V_R = \{1,2,\cdots,r\}$←unvisited targets set
2	Step 1 in the first phase← $V_R = \{1,2,\cdots,r\}$
3	End while
4	End

4.2 Heuristic algorithm for the first step

4.2.1 Generation of initial population and diversity optimisation

In the algorithm, this paper uses integer number to number all the targets, and the base is zero. In order to reduce the probability of UAVs destruction, this paper uses the optimal route to all the targets. Since the speed of UAVs is constant, the traveling time is considered as the insertion costs. In the pre-optimisation stage, VNSS uses the insertion method to generate the initial population according to the principle of improved saving algorithm, and the insertion costs of customer point l which are incurred between i and j is $c_{ijl} = c(i,l) + c(l,j) - g \cdot c(i,j) + k \cdot |c(i,l) - c(l,j)|$ [37,38], where $c(i,l) = t(i,l) + s(l)$ and g,k is the random number, $g \in [0,3], f \in [0,1]$. The target points are inserted from $\{0,0\}$, and then the point with the lowest insertion costs is selected by comparison. The new schemes should be tested by the individuals in the current population so as to ensure that new schemes are different from other schemes in the initial population. During the whole process, the new scheme must be verified by random chance constraint after generation. If the scheme does not meet the constraint, the penalty costs p_c will be increased.

4.2.2 Reference set update and subset generation

After the initial population is generated, the scheme in the current population is selected to form a reference set P which contains set ES and set VS. ES expresses the elite solution which represents the solution that the objective function value is less than the average value in the initial population, and VS expresses the variety solution which means the solution with rich route diversity.

Set VS are selected based on many stages. Firstly, the distance between two solutions is equal to the maximum number of arcs of two solutions minus the number of common arcs. Secondly, the diversity distance of one solution is expressed by the minimum value of the distance between which and all solutions in set ES . Thirdly, the diversity distance of all solutions is calculated and those with diversity distance greater than the average value are selected to form set VS.

In the subset generation scheme, two schemes X_1, X_2 are randomly selected in the reference set P , and two new schemes Y_1, Y_2 are generated by combination. Firstly, a crossover point θ is generated randomly. Secondly, the target points before θ in X_1 are retained. The visited targets are deleted according to the target arrangement order of X_2 , and then are copied to the corresponding positions in turn to form a new solution Y_1. The new solution Y_2 is similar. The position of 0 in the scheme is always unchanged [39]. Specific example is as follows: $X_1 = 014065308270$, $X_2 = 068024305710$ and $\theta = 5$. After finishing the subset generation, Y_1 is $0140682035\ 70$ and Y_2 is $0680145032\ 70$. The new solution may be infeasible, and the infeasible solution is modified by penalty function P_e.

4.2.3 Variable neighbourhood search strategy

In this paper, considering the change of the position between the midpoint and the route, three kinds of structures, namely, relocate, exchange and 2-opt, are selected to search the variable neighbourhood of the population scheme in order to make it approach the global optimal gradually from the local optimum in the neighbourhood. For individuals in the population which starts from the first neighbourhood structure, if no improved solution is found within the pre-set neighbourhood search times, the next neighbourhood structure is executed. In the search process, the neighbourhood radius reduction strategy is introduced, that is, the points far away from the neighbourhood to be changed are not included in the neighbourhood structure replacement [40]. In this paper, the neighbourhood search strategy is as follows:

(1) Relocate:

The target i is randomly selected in the current scheme, and point i is reset on both sides of each point in its neighbourhood. When the reset point is the base, a new route can be reset between the two points. As shown in Fig.6 below:

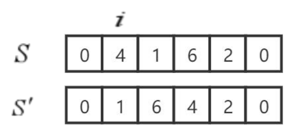

Fig. 6 Example of relocate

(2) Exchange:

Two targets i and j are randomly selected. And then the positions of targets i and j are exchanged. As shown in Fig.7 below:

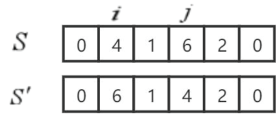

Fig. 7 Example of exchange

(3) 2-OPT:

Two targets i and j are randomly selected. If i and j are in the same route and are not adjacent, their order is exchanged. If they belong to different routes, the sub line is separated where j point is from the scheme and exchange some edges to connect i and j to form four new sub lines. As shown in Fig.8 below:

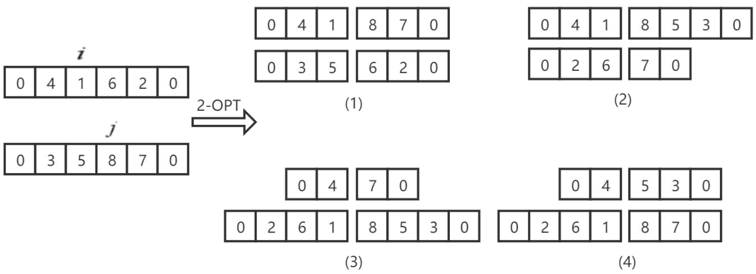

Fig. 8 Example of 2-OPT

4.2.4 Determination of the number of UAVs

Assuming the number of available UAVs is f, the fixed number of UAVs in the first step of algorithm is $f_i(f_i = 1,2,\cdots,f)$. After finding the optimal routes in the case of f_i UAV, one UAV is added and the first step of the algorithm is performed again. And this process is repeated until the total costs of each scheme under all possible UAV numbers are calculated. Among all the schemes, the minimum costs scheme is found in which the number of UAVs is optimal. Then the second step of the algorithm is carried out.

4.3 Failure point return strategy in the second step

Through the equivalent calculation of the chance constrained deterministic model, this paper can get the vehicle capacity limit $\bar{Q}$ which participates in the model and algorithm to calculate the pre-optimal route. Since the shocks by which UAVs are attacked are random, it is possible for UAVs to be destroyed on the route which will increase the costs [41]. Through the Monte Carlo simulation of the random shocks in the pre-optimal route, the actual UAVs' task process can be simulated. The simulation steps are as follows:

Step 1: A route to simulate 100 times is selected. Each simulation randomly generates random numbers in accordance with Poisson distribution, and multiplies the corresponding flight time to simulate the attack time of UAVs.

Step 2: The flight time is recorded when the UAV is destroyed after being attacked by a certain number of shocks.

Step 3: The simulation results of 100 times will be averaged.

Step 4: The failure point which is the time of UAVs destruction is found.

When a failure point occurs, due to the high costs of UAVs destruction, this paper chooses UAVs to return to the base after finishing visiting the targets before the failure point [42]. In this model, this paper assumes that the UAVs will not be destroyed before returning to the base.

4.4 Rescheduling strategy for unvisited targets in the third step

After all the UAVs return to the base before the failure point, the set of unvisited targets is found which are $V_R = \{1,2,\cdots,r\}$, $V_R \in V$. V_R includes all the failure points and all the unvisited targets. When V_R is an empty set, it indicates that all the targets have been visited. If not, it indicates that some targets are not visited in the pre-optimisation stage and they should be rescheduled to be visited in the rescheduling stage. In the third step, because the shocks that UAVs are attacked by are random, the set of the unvisited targets V_R in the first step can be seen as the initial target set of the third step and the method to calculate the optimal routes is the same as that in the first step. More logical descriptions are as follows:

Step 1: The initial target set Q_1 in the first step is $V = \{0,1,2,3,\cdots,i,\cdots,N\}$.

Step 2: The algorithm in the first step is used to obtain the pre-optimal routes.

Step 3: The algorithm in the second step is used to find the failure points.

Step 4: The UAVs return to the base before the failure points and the unvisited targets in the pre-optimization stage comprise $V_R = \{1,2,\cdots,r\}$, $V_R \in V$.

Step 5: The initial target set Q_2 in the third step is V_R .

Step 6: The algorithm in the first step is used to obtain the rescheduled routes for unvisited targets in the third step.

5 Numerical experiment

5.1 Experiment description

5.1.1 The calculation of total costs of UAVs tasks

The model in this paper only considers the costs of UAVs destruction and the costs of unvisited targets. In the rescheduling stage, it should be noted that the new UAVs are needed and the failure may still occur in the rescheduling routes.

In the pre-optimisation stage, the total number of H_f is described as N_{H_f} . Similarly, in the rescheduling stage, the rescheduling route assigned to the UAV k is expressed as H'_k and the total number of H'_k is described as $N_{H'_k}$. Obviously, the number of UAVs activated in the pre-optimisation stage is N_{H_f} and the number of UAVs activated in the rescheduling stage is $N_{H'_k}$. Therefore, as for the costs of UAVs destruction during the travel, it can be described as $c_u \cdot \left(N_{H_f} - N_{H'_k}\right)$ in the pre-optimisation stage and $\sum_{k=1}^{N_{H'_k}} c_u \cdot (1 - P_s(k))$ in the rescheduling stage. At the beginning of this paper, the expected number of unvisited targets for each UAV is found which is $\sum_{i=0}^{|H_f|-1} P_i(f)\left(|H_f| - i\right)$. Since the unvisited targets in the pre-optimisation stage will be visited in the rescheduling stage, there is no costs of unvisited targets in the optimisation phase. Therefore, the costs of unvisited targets is described as

$$\sum_{k=1}^{N_{H'_k}} \left(c_t \cdot \sum_{i=0}^{|H'_k|-1} P_{R_j} P_i(k)\left(|H'_k| - i\right) \right) \quad P_{R_j} = \begin{cases} 1 & j \geq b_f \text{ -1} \\ P_j(f) & j < b_f \text{ -1} \end{cases} \tag{22}$$

Where b_f is the failure point of UAV f and j is the exact point where the UAV f returns to the base.

Above all, the total costs of UAVs tasks can be described as

$$C = c_u \cdot \left(N_{H_f} - N_{H'_k}\right) + \sum_{k=1}^{N_{H'_k}} \left(c_u \cdot (1 - P_s(k)) + c_t \cdot \sum_{i=0}^{|H'_k|-1} P_{R_j} P_i(k)\left(|H'_k| - i\right) \right) \tag{23}$$

$$P_{R_j} = \begin{cases} 1 & j \geq b_f - 1 \\ P_j(f) & j < b_f - 1 \end{cases} \tag{24}$$

5.1.2 Parameter setting

In the cases below, 100 targets are set and 25 UAVs are available. The positions and time windows of the base and targets are the same as that in the Solomon dataset C101 which has been researched in Solomon [43] and Lau *et al.* [44]. The speed of each UAV is assumed to be 0.01 and the frequency of shocks is set as $p = 0.00003$. The probability that each UAV is destroyed after being attacked by i shocks is described as: $C(0) = 0$, $C(1) = 0.1$, $C(2) = 0.4$, $C(3) = 0.7$, $C(4) = 0.8$, $C(i) = 1$ for $i \geq 5$. The costs for one UAV's destruction is $c_u = 1000$, and the costs of one unvisited target is $c_t = 20$.

In order to test the validity of the model in this paper, the result is used to compare with the result of Peng [16]. Peng's study [16] allows UAVs to abort the task when it has been attacked by a certain number of shocks after visiting some targets. In the case of Peng (case 1), all the targets are visited by one of the UAVs in the schedule and 5 UAVs are used in total. With the total cost factors of all UAVs, the costs in total are 1367.1.

5.2 Results of the first step in algorithm

In the case of this paper (case 2), the aborting strategy is cancelled. After the iteration of the Heuristic algorithm for pre-optimisation, the initial optimisation routes of UAVs are obtained. Tables 2-6 display visiting order of the targets and the contribution of each UAV to the total costs. 5 UAVs are used and the total costs for all UAVs are 1969.66. Figure 9 shows the UAVs optimal assignment in the first stage.

In this case, the non-success but successful return probability means the UAV returns to the base successfully without finishing visiting the targets assigned. This index is used to compare with the case in Peng's study in which the non-success but successful return probability is high because of the aborting strategy. In case 2, the non-success but successful return probability of all the UAVs is 0 because this stage does not consider the aborting strategy. The UAVs in this stage only have two situations in the end: one is that the UAV returns to the base successfully after serving all the targets assigned and another is that the UAV has been attacked by many shocks so that it is destroyed and cannot keep executing the task. Therefore, the situation that the UAV does not visit all the targets but returns successfully does not exist. Moreover, because of the lack of the aborting strategy, the total costs of UAVs tasks in this case are higher than case 1.

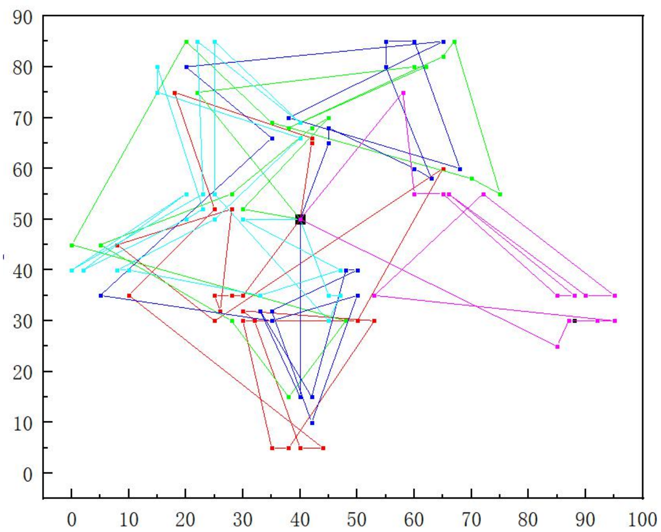

Fig. 9 The optimal assignment in the first stage

Table 2 Targets for the first UAV to visit

Vehicle ID: 001

Number of customers served: 22

Customer	Arrival	Whether time window constraints are met
005	1513	Y
003	1613	Y
017	9063	Y

025	12304	Y
031	19167	Y
053	24534	Y
056	29000	Y
044	41125	Y
046	41408	Y
072	47109	Y
058	50024	Y
060	50324	Y
045	58750	Y
061	60750	Y
088	64104	Y
051	69500	Y
034	74767	Y
022	77219	Y
050	83210	Y
052	83526	Y
049	91500	Y
047	100300	Y

success prob=0.383154

non-success but successful return prob=0.000000

costs for unserved targets and UAV destruction =746.695205

a) In the this and the following tables, Y means that the UAV meets the time window constraint when visiting the target. N means the time window constraint is not met.

Table 3 Targets for the second UAV to visit

Vehicle ID: 002

Number of customers served: 19

Customer	Arrival	Whether time window constraints are met
013	3081	Y
096	6914	Y
095	9700	Y
008	22283	Y
094	28541	Y
092	28902	Y
082	39905	Y
084	40488	Y
011	49469	Y
016	51662	Y
039	56134	Y
064	61729	Y
059	65003	Y
048	66903	Y
036	69649	Y

023	72157	Y
004	75110	Y
002	75471	Y
021	84843	Y
success prob=0.412841		
non-success but successful return prob=0.000000		
costs for unserved targets and UAV destruction=692.154938		

Table 4 Targets for the third UAV to visit

Vehicle ID: 003		
Number of customers served: 22		
Customer	Arrival	Whether time window constraints are met
057	3500	Y
042	5338	Y
055	8724	Y
065	12071	Y
063	12271	Y
041	18800	Y
054	21109	Y
062	23734	Y
040	27781	Y
035	30822	Y
010	35136	Y
015	37752	Y
093	42928	Y
009	50589	Y
085	56562	Y
097	59187	Y
100	59689	Y
099	65200	Y
089	76641	Y
091	77002	Y
001	85300	Y
075	91500	Y
success prob=0.412841		
non-success but successful return prob=0.000000		
costs for unserved targets and UAV destruction=692.154938		

Table 5 Targets for the fourth UAV to visit

Vehicle ID:004		
Number of customers served: 22		
Customer	Arrival	Whether time window constraints are met
020	1000	Y
067	2972	Y

043	4459	Y
032	6813	Y
033	7013	Y
024	10672	Y
007	12865	Y
018	19657	Y
019	20157	Y
027	30712	Y
029	31073	Y
037	37859	Y
030	40643	Y
038	47400	Y
028	50646	Y
014	57602	Y
006	60010	Y
012	64293	Y
026	68200	Y
068	71402	Y
066	73939	Y
069	82800	Y

success prob=0.455802

non-success but successful return prob=0.000000

costs for unserved targets and UAV destruction=637.849658

Table 6 Targets for the fifth UAV to visit

Vehicle ID: 005

Number of customers served: 15

Customer	Arrival	Whether time window constraints are met
098	3081	Y
090	5091	Y
087	5591	Y
081	11328	Y
078	11628	Y
086	14601	Y
076	20424	Y
071	20924	Y
083	32348	Y
074	35107	Y
070	39530	Y
073	39830	Y
079	57500	Y
080	67339	Y

success prob=0.519077

non-success but successful return prob=0.000000

costs for unserved targets and UAV destruction=529.721373

5.3 Results of the second step in algorithm

After simulation (mentioned in section 4.3) based on the routes in case 2, the failure points and unvisited targets of each route are shown in Table 7. Take route 1 as an example, the first UAV will be destroyed at time 69356 which is between target 88 and target 51. Therefore, the failure point of route 1 is target 51 and the UAV has to return to the base after serving target 88. All the targets after failure points have to be rescheduled to be visited. In total, 28 target points are not visited and they will be visited in the rescheduling stage. Although the unvisited targets are not served by UAV, their time windows have been opened, which will cause a waste of time and increase the cost of rescheduling. Therefore, the time windows of these targets will be reopened and the length of the time windows will remain unchanged when the route is rescheduled.

Table 7 The targets needed to be rescheduled of each route (unvisited targets)

Route	Destroy Time	Start Target	End Target	Re-Optimized Targets
1	69356	88	51	51,34,22,50,52,49,47
2	61212	39	64	64,59,48,36,23,4,2,21
3	63512	100	99	99,89,91,1,75
4	59868	14	6	6,12,26,68,66,69
5	48345	77	79	79,80

5.4 Results of the third step in algorithm

The rescheduling optimal routes based on case 2 are shown in Table 8-10. 3 UAVs are used in total. Each table displays the order of the targets, the probability of successful visiting all the specified targets and safely returning to the base, and the contribution of each UAV to the total costs. Concerning all the factors which incur the costs, the costs in total are 927.87. In this case, the strategy of rescheduling optimal routes is the same as that in case 2. Figure 10 shows the actual routes of UAVs in two stages, which is the complete mission. The solid lines indicate the actual routes which the UAVs travelled in the first stage. The UAVs return to the base before the failure points. The dotted lines indicate the optimal routes in the second stage, in which UAVs are rescheduled to visit those unvisited targets in the first stage.

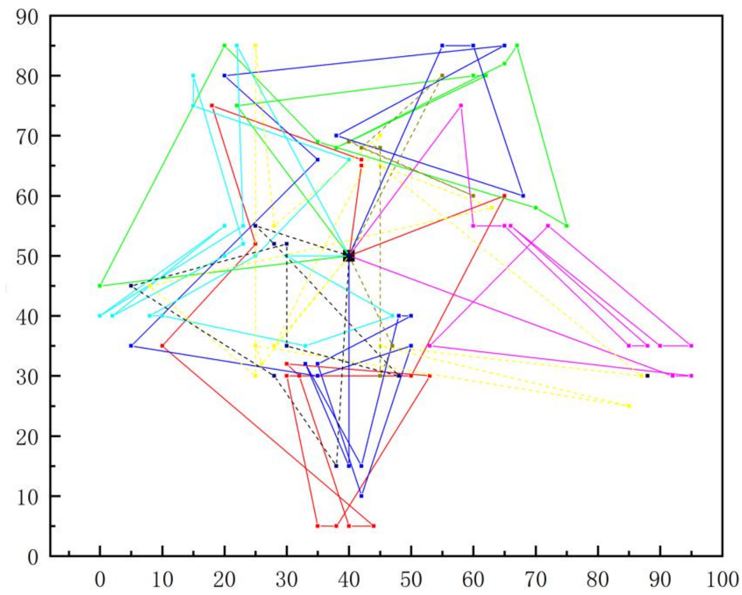

Fig. 10 The actual routes in the first stage and the second stage

Table 8 Targets for the first UAV to visit

Vehicle ID: 001		
Number of customers served: 14		
Customer	Arrival	Whether time window constraints are met
004	1900	Y
005	4093	Y
028	7134	Y
026	9475	Y
027	9836	Y
020	16618	Y
017	18818	Y
002	22849	Y
001	23049	Y
022	26349	Y
012	27849	Y
014	32700	Y
006	34412	Y
reliability=0.817402		
non-success but successful return prob=0.000000		
costs for unserved targets and UAV destruction=205.264531		

Table 9 Targets for the second UAV to visit

Vehicle ID: 002		
Number of customers served: 7		
Customer	Arrival	Whether time window constraints are met
016	2500	Y
013	2800	Y

018	4603	Y
021	6258	Y
019	7300	Y
024	11200	Y
025	11739	Y
reliability=0.884813		
non-success but successful return prob=0.000000		
costs for unserved targets and UAV destruction=119.458309		

Table 10 Targets for the third UAV to visit

Vehicle ID: 003		
Number of customers served: 8		
Customer	Arrival	Whether time window constraints are met
009	1581	Y
010	3553	Y
011	3853	Y
015	8370	Y
007	10610	Y
008	10910	Y
003	14510	Y
023	14934	Y
reliability=0.412841		
non-success but successful return prob=0.000000		
costs for unserved targets and UAV destruction=603.143357		

5.5 Result analysis

The total costs of UAVs tasks calculated by the algorithm in this paper are 1274.55 which is comprised of two parts. The first part is all the UAVs set out from the base and return to the base before the failure points. In this process, the costs only include the costs of the UAVs destruction. In the second part, the costs include the costs of the UAVs destruction and the costs of unvisited targets in the rescheduled routes. The costs of the first part are 346.68 and that of the second part is 927.87. Comparing to the case in Peng's study [16], the case with failure point return strategy and rescheduling strategy reduces 6.8% of the total costs which means the model of this paper can reduce the costs and have high reliability of UAVs routing optimization problem.

In fact, when a UAV flies for a long time, the probability of its destruction will increase. Generally, the costs of UAV destruction are high. Therefore, the failure point return strategy reminds UAVs to return to the base which reduces the risk of UAVs destruction. However, the failure point return strategy will increase the number of unvisited targets and then add the costs of unvisited targets. Therefore, the rescheduling strategy is used to cut down the costs. And these are the mechanism in this paper to reduce the total costs of UAVs tasks so as to improve the reliability of UAVs routing optimization problem.

5.6 Sensitivity analysis

In practical cases, the cost of UAV destruction and the cost of unvisited targets are different in different situation. For the strictness of the experiment, experiment has been conducted to study the change of the total cost result from the variety of the UAV destruction cost and unvisited target cost. Eight data groups are produced in the experiment and there are eight data pairs in each data group, which has sixty-four data pairs in total. In each data group, the cost of UAV destruction is fixed which is 10, 20, 40, 60, 80,100, 500 and 1000 respectively. And the cost of unvisited targets is 10, 20, 40, 60, 80,100,500,1000 respectively in each data group. The detailed data are shown in Table 11.

Table 11 The detailed data

c_u	c_t	**Total cost**	c_u	c_t	**Total cost**	c_u	c_t	**Total cost**
10	10	51.753275	60	10	119.748512	500	10	526.705646
10	20	65.667843	60	20	147.873386	500	20	711.321412
10	40	90.524118	60	40	189.199774	500	40	760.97214
10	60	112.69601	60	60	203.479615	500	60	805.392021
10	80	137.05072	60	80	238.453087	500	80	841.290821
10	100	157.48943	60	100	238.125125	500	100	878.528923
10	500	598.17324	60	500	691.290966	500	500	1182.9917
10	1000	1206.1844	60	1000	1300.46678	500	1000	1993.16226
20	10	64.400993	80	10	160.652825	1000	10	865.82423
20	20	84.853405	80	20	184.064237	1000	20	1274.55167
20	40	109.86038	80	40	220.431514	1000	40	1386.81644
20	60	137.05778	80	60	247.149643	1000	60	1441.09683
20	80	160.48585	80	80	272.239881	1000	80	1175.02118
20	100	183.49657	80	100	271.23132	1000	100	1534.59944
20	500	624.42087	80	500	781.625604	1000	500	2556.14692
20	1000	1240.6414	80	1000	1363.81118	1000	1000	2781.46104
40	10	101.39449	100	10	171.858381			
40	20	122.62155	100	20	216.591882			
40	40	147.34008	100	40	245.226493			
40	60	157.81718	100	60	248.944328			
40	80	197.59005	100	80	276.906147			
40	100	223.34355	100	100	335.669516			
40	500	705.11321	100	500	832.347326			
40	1000	1215.6146	100	1000	1324.49002			

Using the data in Table 11, the population mean and population variance of total cost are calculated to study the impact of the cost of UAV destruction and the cost of unvisited target respectively on the total cost. Seventeen data groups are calculated which has. The first data group is all of the total cost in table 10. In other sixteen data group, each data group fixes one cost value and changes another whose values are 10, 20, 40, 60, 80,100,500 and 1000 respectively. Among the sixteen groups, the fixed cost of each group is the UAV destruction cost values of 10, 20, 40, 60, 80,100,500 and 1000 respectively and the unvisited target cost values of 10, 20, 40, 60, 80,100,500 and 1000 respectively. The results of population mean and population variance are displays in Table 12.

In Table 12, if the cost of unvisited target is fixed and the cost of UAV destruction varies, the average total cost varies from 302.4 to 1626.9. If the cost of UAV destruction is fixed and the cost of unvisited target varies, the average total cost varies from 257.8 to 1553.2. These two value range are similar. And compared to each average total cost when the cost of UAV destruction is fixed, each average total cost when the cost of unvisited target is fixed with same value is similar as well. Also, it is obvious that the total cost will increase with the increase of one cost when the other is fixed.

Table 12 Mean Analysis and Variance Analysis

c_u	c_t	AVERAGE	AVRP
~	~	607.7086161	369952.3411
10	~	302.4423906	144049.0448
20	~	325.6521642	147790.8015
40	~	358.8543446	138193.5533
60	~	391.0796553	146565.1083
80	~	437.6507763	156957.1092
100	~	456.5042616	145976.8066
500	~	962.5456151	181365.9834
1000	~	1626.939721	400596.6885
~	10	257.7922949	72775.82115
~	20	350.9431738	159297.2322
~	40	393.7963681	181028.6808
~	60	419.2041874	192551.3585
~	80	412.3797196	127402.5821
~	100	477.8104853	206460.7405
~	500	996.5137303	376945.0861
~	1000	1553.228971	273289.8762

Considering the scale of the data groups, the differences between each data group in Table 11 are not the same. In order to explain the problem more rigorously, two data groups are selected for detailed analysis. In each data group, the fixed cost value is 10, the other cost value is 10 to 100 during which the distance is 10 and 100-1000 during which the distance is multiplied by 10. The results of detailed analysis are shown in Table 13 which also involves the number of assigned UAVs and the unvisited targets.

Table 13 The detailed Analysis

c_u	c_t	**Total cost**	**Num of assigned UAVs**	**Num of unvisited targets**
10	10	51.753275	5	0
20	10	64.400993	5	0
40	10	101.394497	5	0
60	10	119.748512	5	0
80	10	160.652825	4	1
100	10	171.858381	4	1
200	10	301.130133	4	3
300	10	329.610621	3	9
400	10	538.268707	3	7
500	10	526.705646	3	8
600	10	615.73033	3	8
700	10	501.634276	2	28
800	10	569.814066	2	27
900	10	331.538299	1	55
1000	10	365.82423	1	55
10	10	51.753275	4	0
10	20	65.667843	4	0
10	40	90.524118	4	0
10	60	112.696095	4	0
10	80	137.050721	4	0
10	100	157.489431	4	0
10	200	265.027023	4	0
10	300	377.164533	4	0
10	400	488.016434	4	0
10	500	598.173236	5	0
10	600	738.81193	5	0
10	700	853.051902	5	0
10	800	969.734371	5	0
10	900	965.440262	5	0
10	1000	1206.184406	5	0

According to the data above, there are three conclusions can be found.

Firstly, there is no significant difference between the impact of the cost of UAV destruction and the cost of unvisited target on total cost. When the cost of UAV destruction increases and the cost of unvisited target remains unchanged, the total cost increases; When the cost of unvisited target increases and the cost of UAV destruction remains unchanged, the total cost increases. And the growth rate of the total cost is close in the two cases.

Secondly, fix the cost of unvisited target to 10, and then observe the impact of the cost of UAV destruction change on the optimal scheme. It is found that with the gradual increase of the cost of UAV destruction, the number of assigned UAVs decreased gradually and the number of unvisited target points increased gradually. When the value of the cost of UAV destruction is 900 and 1000, there is only one UAV in the optimal scheme, and 55 target points are not assigned. It can be imagined that when the cost of UAV destruction is high enough that the expected loss cost of UAV destruction exceeds the sum of the unvisited costs of all target points, it is obvious that assigning no UAV is the best solution.

Thirdly, fix the cost of UAV destruction to 10, and then observe the impact of the change of the cost of unvisited target on the optimal scheme. It is found that the only characteristic is that when the cost of unvisited target is less than 500, there are four UAVs in the optimal scheme; When the cost of unvisited target is greater than or equal to 500, there are 5 UAVs in the optimal scheme.

6 Conclusions

The routing strategy (optimal routes, aborting policy and rescheduling strategies) of UAVs are studied in this paper from a view of mission reliability. Each UAV is arranged to visit the assigned targets to them. During the travel, the UAVs will be attacked by shocks, which will lead to the failure of UAVs' missions. In this case, the reliability of UAVs will decrease and the costs will increase because of the destruction of UAVs and those unvisited targets. In this paper, inspired by CVRPSD, the task process of UAV is described as a two-stage model which involves the pre-optimization stage and rescheduling stage. The UAV visits the assigned targets according to the pre-optimal route and returns to the base before finishing its visit and the failure point in the pre-optimization stage. Those unvisited targets in the pre-optimization stage are rescheduled by dispatching new UAVs to visit in the rescheduling stage. To address the optimization problem of UAVs' routes, a three-step VNSS algorithm is proposed. The first step is to find the pre-optimal routes which combines the variable neighbourhood search (VNS) and scatter search (SS). The second step is to calculate the failure points. The third step is to reschedule the optimal routes to the unvisited targets in the pre-optimized route.

In addition, in order to illustrate the proposed model, examples are presented to show the comparison between the total costs of the case in Peng's study [16] and that in this study. The results show that the total costs of UAVs' tasks can be reduced 6.8% when using VNSS and rescheduling strategy to find the optimal routes of UAVs. Reducing the total costs indicates that VNSS and rescheduling strategy can effectively reduce the flight time of UAVs and the probability of UAVs destruction. In this way, the total costs of UAVs tasks will decrease while the reliability of UAVs routing optimization problem will increase. The examples show that VNSS and rescheduling strategy are significantly useful in the application to the practice. And the sensitivity analysis is conducted to ensure the strictness of the study.

Future research can be conducted in the following directions. The value of the Poisson distribution parameter can be varied. For example, the value of the Poisson distribution parameter is treated as a variable depends on the environmental conditions. Moreover, it is innovative to jointly consider the visiting task of UAVs and some other kinds of UAV tasks, such as the attacking missions.

Acknowledgement The work has been supported by National Natural Science Foundation of China (No. 71802021, No. 71801013, No. 71803029, No. 72001027).

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