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NEW COOPERATIVE TARGET ALLOCATION METHOD FOR THE TYPICAL TASKS OF UAVS BASED ON A DISCRETE SHEEP OPTIMIZATION ALGORITHM

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Abstract. *As the traditional heuristic algorithm cannot solve the problem of multi-UAVs coordinated global target allocation perfectly, it is difficult to find a reliable initial allocation scheme and the convergence rate is not ideal. In order to solve these problems, a multi-UAVs coordinated global target allocation method based on discrete sheep optimization algorithm is proposed. Firstly, with the typical multi-UAVs coordinated attack task as the research background, the UAVs' fuel consumption cost, damage cost and revenue cost are taken as optimization indicators. Meanwhile, the target allocation model is established by considering the flight distance, flight time, load size, and target execution order of the UAVs. Then the penalty function method is used to deal with partially restrained condition to build a fitness function and the discrete sheep optimization algorithm which is discretized and combined with genetic algorithms is used as well to solve the problem. Finally, the simulation results show that the discrete sheep optimization algorithm for multi-UAVs coordinated global target allocation has the advantages of faster convergence rate and better stability compared with the genetic algorithm, and the allocation scheme with lower integrate-cost can be obtained in different scenarios, which can better solve the problem of multi-UAVs coordinated global target allocation.*

Keywords: Multi-UAVs collaboration, Target allocation, Sheep optimization algorithm, Genetic algorithm

1. **Introduction.** With the development and maturity of UAV technology and the continuous improvement of intelligent level, UAV will become the leader of the future sky and the main equipment of different countries' armed forces in the world [1], and it has great combat potential in the future battlefield. According to the trend of the informationization, networking and systematic antagonism of the modern war, using a single UAV to carry out intelligence reconnaissance, battlefield combat and other tasks could not meet the new requirements [2]. Therefore, it has become an inevitable tendency that multi-UAVs are used to carry out cooperative combat tasks for multiple targets [3]. Due to the complexity of the combat environment and the increase of UAVs' number, multi-UAV coordinated target allocation method is particularly important for operational efficiency improvement. And it is the key technology for multi-UAVs to realize autonomous cooperation, which determines the practicability of multi-UAVs' mutual cooperation and reasonable target allocation [4].

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In recent years, the research on multi-UAVs target allocation has been widely concerned. The commonly used methods include mathematical programming, negotiation-based method and heuristic algorithm. Mathematical programming [5] is a deterministic method which can solve the target allocation in a centralized way. This method requires specific research objects and adjustable mathematical models. Moreover, the capacity of computation should increase exponentially when the model scale is too large. Negotiation-based method belongs to the distributed mission planning technology, and it often uses contract network [6-8] and auction algorithm [9-11]. This kind of method is suitable for task allocation and decision-making in these situations which have strong uncertainty, high dynamic and critical real-time requirements. The heuristic algorithm represented by particle swarm optimization algorithm [12-14], genetic algorithm [15-18], simulated annealing algorithm [19], ant colony algorithm [20], grey wolf algorithm [21,22] has the advantages of low computational complexity, flexible application and easy implementation. Because of this, it is widely used to solve the target allocation problem. In contrast, the traditional heuristic algorithm is difficult to find a reliable initial allocation scheme and the convergence speed is not ideal.

Sheep optimization [23] was proposed by Qu et al. as a new type of swarm intelligence algorithm which simulates sheep foraging behaviour. From the core of swarm intelligence algorithm, sheep optimization designs three corresponding strategies named global search, local development and jump out of local optimum by simulating three behaviors included sheep leading, sheep interaction and shepherd supervision. [23] validated sheep optimization can obtain higher quality solutions, faster convergence speed and better stability by comparing with particle swarm optimization algorithm. However, the common sheep optimization searches every sheep based on a continuous space (interval), which cause the sheep's initial position and position updating mode are both continuous functions, while the variables in multi-UAV cooperative target allocation problem are discrete. In addition, the grazing operation has a great influence on the stability of the algorithm to solve target allocation problem. To solve the above problem, in this paper, the shepherd supervision mechanism is combined with the genetic algorithm. Each sheep is regarded as a chromosome in the genetic algorithm, and the reinitialization is improved to the same chromosome gene crossover operation. Then algorithm stability and the ability to jump out of the local optimum can be guaranteed.

Traditional heuristic algorithms suffer from unreliable optimal solutions and slow convergence rates. To address these problems, we propose a target allocation model with multi constraint conditions based on the characteristics of multi-UAVs collaborative global target allocation method. We adopt sheep algorithm for optimization and do simulation verification. The rest of the paper is organized as follows.

Section 2 establishes an appropriate target allocation model. Section 3 proposes a global target allocation method based on discrete sheep optimization (SO) to address the global target allocation problems of multi-UAV cooperative task execution. The simulation experiments and discussion of results are presented in Section 4. Finally, Section 5 concludes the work and suggests some directions for future studies.

2. **Model of Multi-UAVs Target Allocation.**

In this section, an appropriate target allocation model is established in accordance with the mission background. And on the basis of target allocation model, we established a target allocation cost function in accordance with the requirement of multi-UAV's target allocation model as an index to evaluate the quality of allocation result.

2.1. **Description of target allocation problem.** The main task of multi-UAVs target allocation is to assign appropriate targets or target sequences to each UAV based on known battlefield environment information and mission requirements, and to complete the task while ensuring the highest overall combat effectiveness of the UAV and resource consumption to a minimum. In this paper, we choose cooperative attack tasks on multiple targets executed by multi-UAUs as research background to establish a target allocation model. This model effectively solves the problem of large computational load of traditional combinatorial optimization methods. Through the establishment of the model of the priority, timing relationship and constraints of the tasks performed by the UAV, the optimization algorithm is used to solve the high-dimensional optimization problem. Because the model can be adjusted according to the actual task requirements, it is suitable for a wider range of scenarios.

Suppose the number of our UAVs is u $(u \geq 1)$, $U = \{U_1\ U_2\ \ldots\ U_u\}$. And certain target number of the enemy is t $(t \geq 1)$, $T = \{T_1\ T_2\ \ldots\ T_t\}$. The flight performance and load of each aircraft are different. Different targets also have different attack values and resistance abilities.

Because both the UAV number and target number are uncertain in actual combat, this paper establishes target allocation model for three typical cases:

1) when $u = t$, UAVs are required to correspond to the targets one by one, the model is simple and there are few cooperative constraints;
2) when $u > t$, only one target will be allocated to each UAV, so there is a situation that multiple UAVs attack one target in cooperation. In this case, the time coordination requirements for UAVs formation when having the same target are high;
3) when $u < t$, each target is assigned only once, so there is a case that one UAV attacks multiple targets. In this case, the assigned targets need to follow the timing constraints of task execution.

When making target allocation, the corresponding relationship between UAVs and targets is determined by decision variables, and its definition is shown in Formula (1):

$$x_{ij} = \begin{cases} 0 & U_i \text{ do not attack } T_j \\ 1 & U_i \text{ attack } T_j \end{cases} \quad (i \in [1, u],\ j \in [1, t]) \tag{1}$$

For different quantitative relationships, decision variables can be expressed as:

$$x_{ij} = \begin{cases} x_{ij} & & u = t \\ x_{i'j} & i' = [i_x, \ldots, i_y],\ x, y \in [1, u] & u > t \\ x_{ij'} & j' = [j_p, \ldots, j_q],\ p, q \in [1, t] & u < t \end{cases} \tag{2}$$

In Formula (2), i' represents the serial number of the UAV which attacks the target j and j' represents the serial number of the target which is attacked by the UAV i.

For the multi-objective optimization problem, it is necessary to establish objective function as the optimization index to evaluate the results of target allocation. The optimization indexes considered in this paper include the fuel consumption cost of UAVs, the damage cost and the income cost when UAVs attack the targets. At the same time, they need to meet the constraints of UAVs flight distance, flight time, load size and target execution order.

2.2. **Cost and income index.** In order to maximize the overall efficiency of multi-UAV cooperative operations, the fuel consumption cost and the damage cost of UAVs should be as small as possible, while the revenue cost when UAVs attack the target should be as high as possible.

When UAV completes its mission, we need to consider the fuel consumption problem which is related to the flight range and flight time. Assuming that the UAV's flight speed is fixed, the shorter the flight distance is, the less the fuel consumption is. The fuel consumption cost can be expressed by the flight range. Therefore, the total fuel consumption cost can be expressed as:

$$f_F = \sum_{i=1}^{u} \sum_{j=1}^{t} d_i(T_j, T_{j+1}) \tag{3}$$

In Formula (3), $d_i(T_j, T_{j+1})$ represents the distance from the jth target to the $(j+1)$th target assigned by UAVs. It indicates the distance from the starting point to the first target if the value of j is 1. When implementing target pre assignment, we use the linear distance between the UAV positions and target points to represent the specific flight range which cannot be predicted.

When the UAVs attack the targets, it will be affected by the enemy's fire, terrain, obstacles and other threats in the flight environment. Minimizing the damage cost can ensure that the UAV receives the minimum threat in the mission process.

Assuming that the damage probability when a UAV (U_i) attacks the target (T_i) is h_{ij}, the damage cost of all UAVs is

$$f_A = \sum_{i=1}^{u} \sum_{j=1}^{t} x_{ij} h_{ij} \tag{4}$$

Attack profit cost refers to the target value profit that can be obtained when a UAV attacks its target. In order to calculate the target function value conveniently, the target residual value is used to evaluate the target attack revenue cost which takes maximization as a goal.

Assuming the kill probability when a UAV (U_i) attacks a target (T_i) is p_{ij} and the value of the target (T_i) is v_j, then the attack profit cost of all UAVs is

$$f_V = V_{all} - \sum_{i=1}^{u} \sum_{j=1}^{t} x_{ij} p_{ij} v_j \tag{5}$$

It is impossible to ensure that every index can reach the optimal value in actual combat. Therefore, the normalization method is used to deal with different indexes according to the relative weight of each objective for multi-object problem. Then the problem can be transformed into a single objective optimization problem. The optimal objective function of multi-UAVs cooperative target allocation can be expressed as follows:

$$\min f = c_1\alpha_1 f_F + c_2\alpha_2 f_A + c_3\alpha_3 f_V \tag{6}$$

In Formula (6), α_1, α_2, α_3 are scaling factors which can ensure the value of each generation is at the same level. c_1, c_2, c_3 are the weight coefficients, which indicate the importance of each optimization index. The value range is $[0, 1]$ and meets the equation $c_1 + c_2 + c_3 = 1$. The larger the c_1, the shorter the flight distance, and the lower the total fuel consumption; The larger c_2 indicates that the UAV is less threatened during the mission; The larger c_3 indicates the greater target value gain that the UAV can obtain when attacking target. Different values reflect different decision preferences of the commander.

2.3. **Constraint analysis.** Multi-UAVs cooperative target allocation is a complex multi constraint optimization problem. The constraints considered in this paper [16,24] include:

1) Maximum range constraint

The single flight distance of UAV is limited because of the onboard fuel limitation. Assuming that the total flight distance of the UAV (U_i) is L_i and $L_i^{\max}$ represents the maximum flight distance of the UAV (U_i), then the total flight distance of the UAV to perform the mission shall be less than its maximum limit, i.e.,

$$L_i < L_i^{\max} \quad (\forall U_i \in U) \tag{7}$$

2) Maximum execution capability constraint

The number of ammunitions that can be carried by each UAV is limited by the load capacity. Assuming that each ammunition can only attack the target once, Num_i is the maximum payload of the UAV (U_i), the number of targets that can be attacked by the UAV must be less than or equal to its maximum execution capacity, i.e.,

$$\sum_{j=1}^{t} x_{ij} \leq Num_i \tag{8}$$

3) Target execution order constraint

When cooperative attack is taken, the important targets need to be attacked first, and the priority of some specific targets is also higher than others. Assuming that the priority of the target T_i is greater than the target T_j, the execution order shall meet the following requirements:

$$t_j > t_i + \Delta t \tag{9}$$

In Formula (9), t_i, t_j are the time when the target T_i and the target T_j are attacked respectively, and Δt is the minimum time interval between the two targets.

4) Decision variable constraints

Because the relationship between UAV number and target number is different, the constraints on UAVs and targets are different when target allocation is executed. When $u > t$, each UAV attacks at least one target; when $u < t$, each target was attacked at least once. The constraints can be expressed as:

$$\begin{cases} \sum_{i=1}^{u} x_{ij} = 1 \quad j = 1, 2, \ldots, t \quad u > t \\ \sum_{j=1}^{t} x_{ij} = 1 \quad i = 1, 2, \ldots, u \quad u \geq t \end{cases} \tag{10}$$

3. Coordinated Global Target Allocation for UAVs Based on Discrete Sheep Optimization Algorithm.

In this section, a global target allocation method based on discrete sheep optimization (SO) is proposed to address the global target allocation problems of multi-UAV cooperative task execution.

3.1. Introduction of the SO algorithm.

Sheep optimization realizes fast global exploration by simulating the bellwether and makes the sheep approach the known global optimal solution quickly. Through the mutual movement of sheep to achieve local development, further speed up the convergence and the shepherd supervision mechanism is applied to judging whether the local optimal is entered and quickly jumps out of the local optimal solution.

3.1.1. *The leader of bellwether.*

The bellwether refers to the sheep with the optimal fitness function value in the flock, and the bellwether lead refers to the behavior of each sheep moving towards the bellwether. The corresponding global exploration mechanism of the algorithm is to ensure the search performance. The position of the new sheep is only updated when the fitness function value of the new sheep is better than the old sheep.

Figure 1 shows the flow chart of the algorithm for leading the sheep. The position of the corresponding sheep is updated when the sheep move to the bellwether.

$$x_i^{new} = x_i^{old} + rand(0,1) \times \left(x_{bellwether} - x_i^{old}\right) \tag{11}$$

where x_i^{new} represents the updated position of the ith sheep, x_i^{old} represents the position which has not been updated of the ith sheep, and $x_{bellwether}$ represents the bellwether.

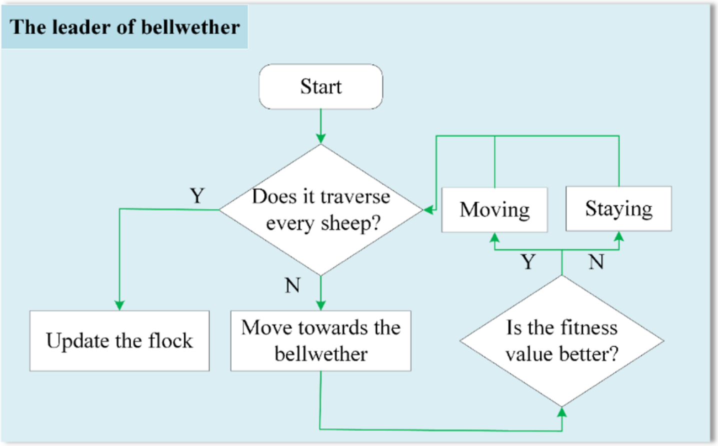


FIGURE 1. The flow chart of the algorithm for the leader of bellwether

3.1.2. *Sheep interaction.* The sheep interaction behavior corresponds to the local development mechanism of the algorithm. Each sheep x_i in the flock will randomly select another random sheep x_j for the sheep interaction strategy. If the fitness value of the selected sheep x_i is better than that of the random sheep x_j, then x_i is updated to the position away from x_j, x_j to the position near x_i, and vice versa. Similarly, to ensure the performance of the search, the position of the new sheep is updated only when the fitness function value of the new sheep is better than that of the old sheep. Figure 2 shows the flow chart of the sheep interaction algorithm.

$$x_i^{new} = x_i^{old} + rand(0,1) \times \left(x_i^{old} - x_j^{old}\right) \tag{12}$$

$$x_j^{new} = x_j^{old} + rand(0,1) \times \left(x_i^{old} - x_j^{old}\right) \tag{13}$$

Formula (12) represents the x_i is updated to the position away from x_j, while Formula (13) represents x_j is updated to the position near x_i.

3.1.3. *Shepherd supervision.* When the fitness function difference between the current generation and the previous generation is less than a threshold ε, the shepherd supervision mechanism is introduced to jump out of the local optimization. Each sheep will be herded by the shepherd with a certain probability p, that is, the sheep will be reinitialized with a probability p. Figure 3 shows the flow chart of the shepherd supervision algorithm.

3.2. **Fitness function structure.** The multi-UAVs cooperative target allocation problem has many constraints, so it is necessary to choose a proper way to get the fitness function. In this paper, penalty function method is used to deal with the constraints, and the corresponding penalty function is as follows.

1) Maximum range

After the target allocation, if the flight distance of a UAV exceeds its maximum distance, the UAV will be punished:

$$C_1 = \begin{cases} 0 & L \le L^{\max} \\ l & L > L^{\max} \end{cases} \tag{14}$$

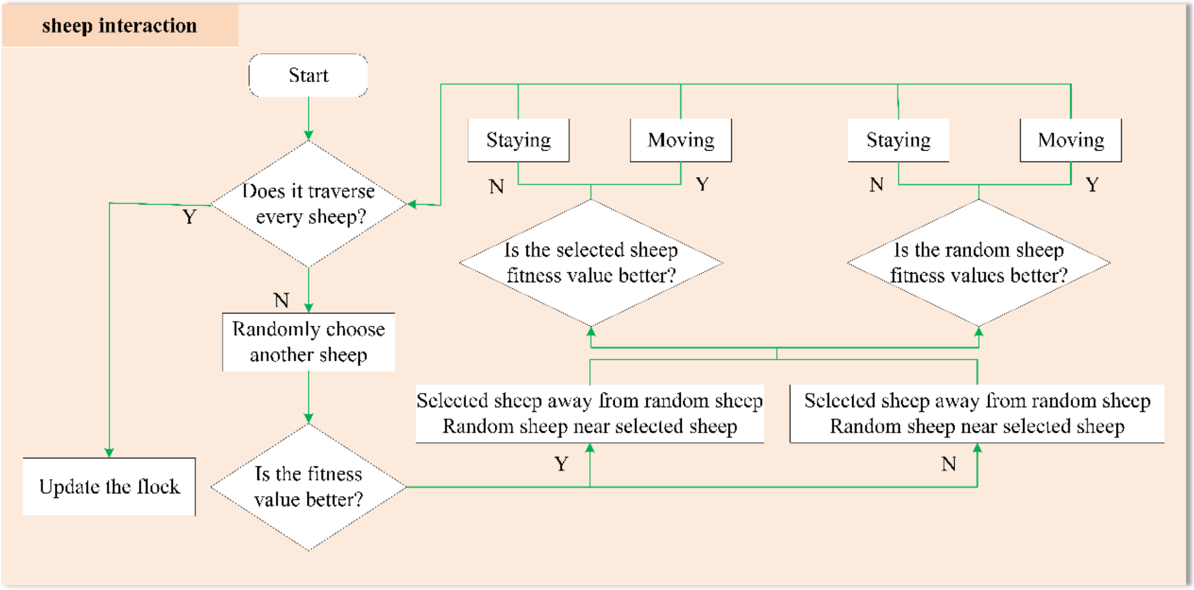


FIGURE 2. The flow chart of the algorithm for sheep interaction algorithm

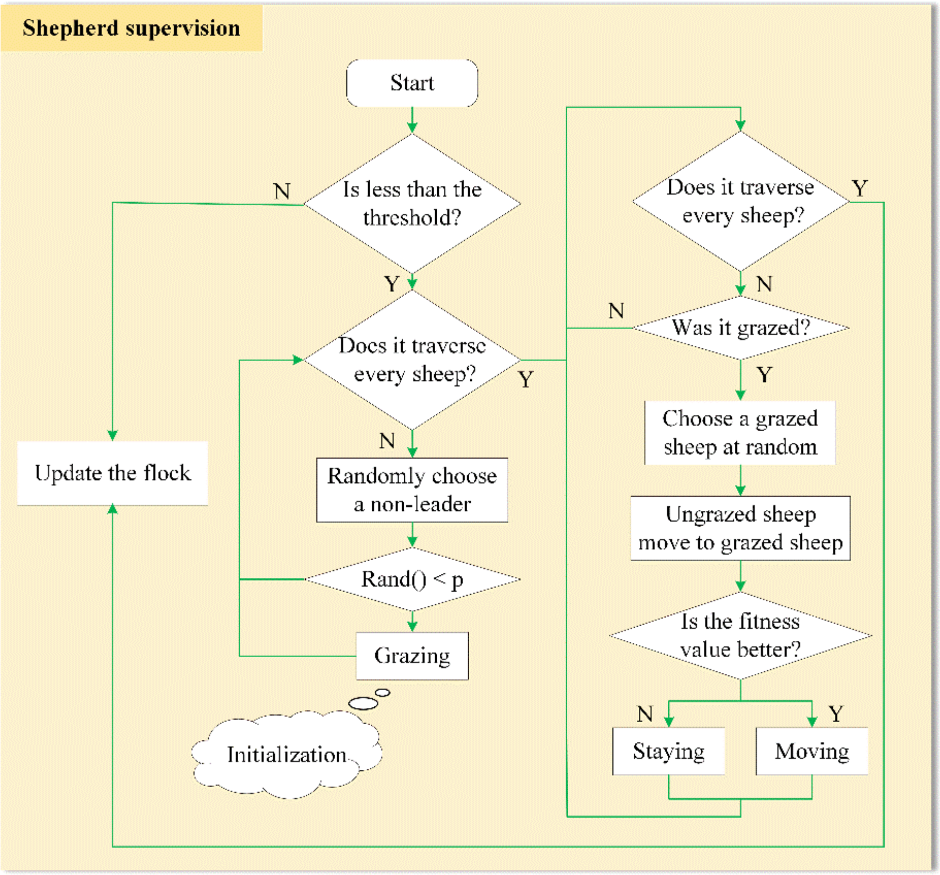


FIGURE 3. The flow chart of the algorithm for shepherd supervision algorithm

In Formula (14), L represents the flight distance of the UAV, $L^{\max}$ represents the maximum flight distance, l represents the penalty value imposed when the maximum range constraint is not satisfied.

2) Maximum execution capacity

After the target allocation, if the flight distance of a UAV exceeds its maximum execution capability constraint, it will be punished:

$$C_2 = \begin{cases} 0 & num \leq Num \\ n & num > Num \end{cases} \tag{15}$$

In Formula (15), num represents the target number allocated by the UAV, Num represents the explosive payloads of the UAV, and n represents the penalty value imposed when the maximum execution capability constraint is not satisfied.

3) Target execution order

After the target allocation, if a UAV does not meet the target execution order constraint, it will be punished:

$$C_3 = \begin{cases} 0 & \text{the order constraint is satisfied} \\ m & \text{the order constraint is not satisfied} \end{cases} \tag{16}$$

After using penalty function method to deal with multiple constraints, the fitness function of sheep optimization to obtain the optimal target allocation scheme can be expressed as follows:

$$\begin{aligned} & fitness = f + C \\ & \begin{cases} f = c_1\alpha_1 f_F + c_2\alpha_2 f_A + c_3\alpha_3 f_V \\ C = C_1 + C_2 + C_3 \end{cases} \end{aligned} \tag{17}$$

In Formula (17), f is the target function value of a sheep, C represents the penalty term, and it means that the sheep is feasible when C is 0.

3.3. **Sheep initialization.**

When using discrete sheep optimization to solve multi-UAVs cooperative target allocation problem, we need to choose the appropriate initialization method which directly affects the search efficiency and the result of the assignment.

In the discrete sheep optimization, each sheep represents an alternative solution, and the whole sheep update the position to search for the optimal solution through the leading of the sheep, the interaction of the sheep and the shepherd supervision [23]. According to the size relation and constraints between UAVs and targets, this paper adopts a flexible initialization method to set up the first-generation sheep. The solution dimension of each sheep is determined according to the current target allocation. If the solution dimension is N_c, the value method of N_c is

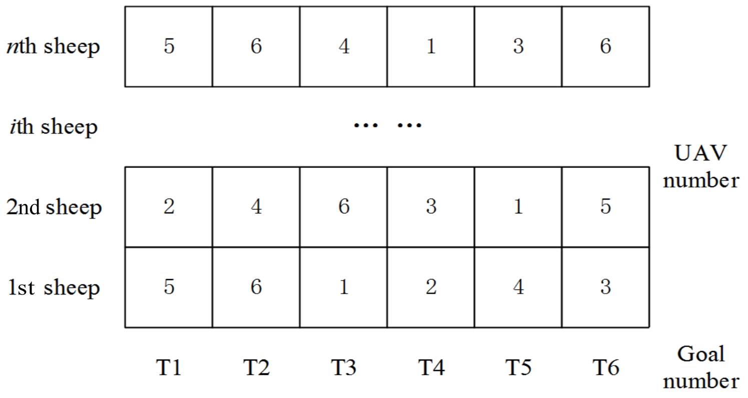
$$N_c = \begin{cases} t & u \leq t \\ u & u > t \end{cases} \tag{18}$$

When the UAV number is bigger than the target number, the solution dimension is the total number of UAVs. When the number of targets to be allocated is bigger than or equal to the UAV number, the solution dimension is the total number of targets to be allocated. The sheep are represented as multidimensional arrays, as shown in Figure 4.

We use $u < t$ ($u = 4$, $t = 8$) as an example, if the final allocation result is the solution represented by the first sheep in Figure 4(b), the corresponding decision variable matrix is as follows:

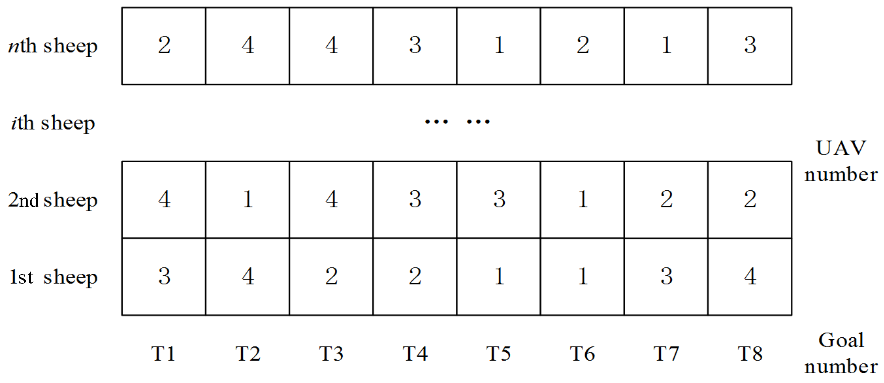
$$X = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{19}$$

This initialization method can meet the constraints of decision variables when the target is allocated. The initial population quality directly affects the result of offspring evolution.



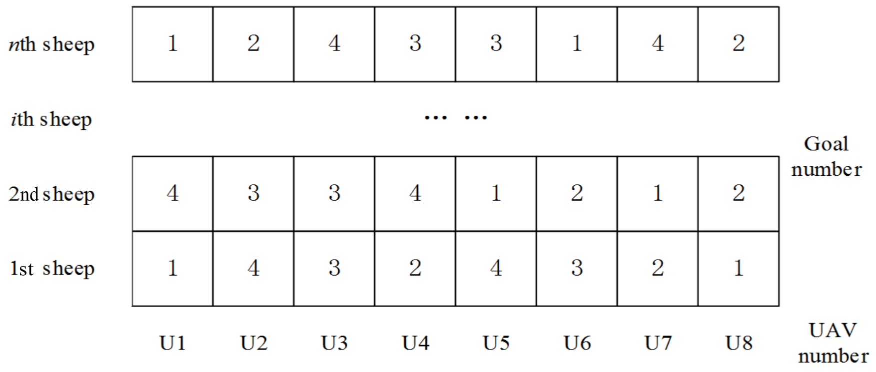
*n*th sheep	5	6	4	1	3	6
*i*th sheep	… …					
2nd sheep	2	4	6	3	1	5
1st sheep	5	6	1	2	4	3
	T1	T2	T3	T4	T5	T6

(a) $u = t$ $(u = t = 6)$



*n*th sheep	2	4	4	3	1	2	1	3
*i*th sheep	… …							
2nd sheep	4	1	4	3	3	1	2	2
1st sheep	3	4	2	2	1	1	3	4
	T1	T2	T3	T4	T5	T6	T7	T8

(b) $u < t$ $(u = 4,\ t = 8)$



*n*th sheep	1	2	4	3	3	1	4	2
*i*th sheep	… …							
2nd sheep	4	3	3	4	1	2	1	2
1st sheep	1	4	3	2	4	3	2	1
	U1	U2	U3	U4	U5	U6	U7	U8

(c) $u > t$ $(u = 8,\ t = 4)$

FIGURE 4. Population initialization

In order to ensure the effectiveness of the scheme, each scheme is judged after the initial population is obtained. The sheep will be reinitialized unless it can satisfy the constraint.

3.4. **Discrete strategy.** In this paper, sheep movement is improved to a mode that generates random integer to update positions. Assuming that a sheep performs leading operations as a bellwether, the position update method of common sheep is as follows:

$$x_i^{new} = x_i^{old} + rand(0,1) \times \left(x_{bellwether} - x_i^{old}\right) \tag{20}$$

The updating method with bellwether leading operation of the discrete sheep optimization is as follows:

$$x_i^{new} = x_i^{old} + randi\left(x_{bellwether} - x_i^{old}\right) \tag{21}$$

A small change in each dimension of the solution in the target allocation problem will have a great impact on the fitness function value, and the sheep reinitialization after grazing will greatly affect the stability of the algorithm. In this paper, the shepherd supervision mechanism is combined with the genetic algorithm. Each sheep is regarded as a chromosome in the genetic algorithm, and the reinitialization is improved to the same chromosome gene crossover operation. Then algorithm stability and the ability to jump out of the local optimum can be guaranteed. If a sheep is grazing when $u = t = 6$, the operation is shown in Figure 5.

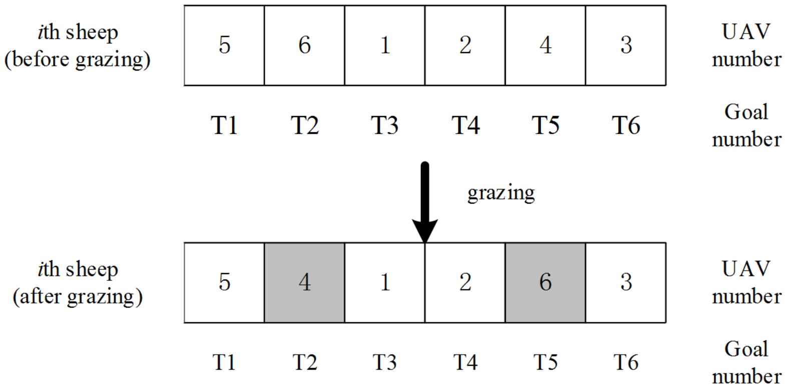


FIGURE 5. Grazing operation

Table 1 shows the steps of multi-UAVs cooperative global target allocation using the sheep optimization. The shepherd supervision mechanism is combined with the genetic algorithm, and the reinitialization is improved to the same chromosome gene crossover operation. The discrete sheep algorithm flow is shown in Figure 6.

TABLE 1. Steps of discrete sheep algorithm

Steps	Discrete sheep optimization algorithm
1	Algorithm initialization
2	***while*** algorithm termination conditions are not met
3	carried out the leader of bellwether
4	carried out sheep interaction
5	carried out shepherd supervision
6	***end while***
7	Output result

4. **Experiment and Result Analysis.** In order to verify the effectiveness of the sheep optimization in the multi-UAVs cooperative global target allocation problem, we use MATLAB to carry out simulation experiment and compare the performance of sheep optimization with the genetic algorithm (GA).

4.1. **Algorithm initialization.** Assume that there are eight available combat UAVs before operation and eight target points to be attacked. The initial parameter information classification of UAVs and target points is shown in Table 2 and Table 3.

Assuming that UAV has the same kill probability for each target and the damage probability after attacking the targets is shown in Table 4. The algorithm parameter is set as: population size $NP = 50$, maximum number of iterations is 100, threshold $\varepsilon = 10^{-8}$, reset probability $p = 0.2$.

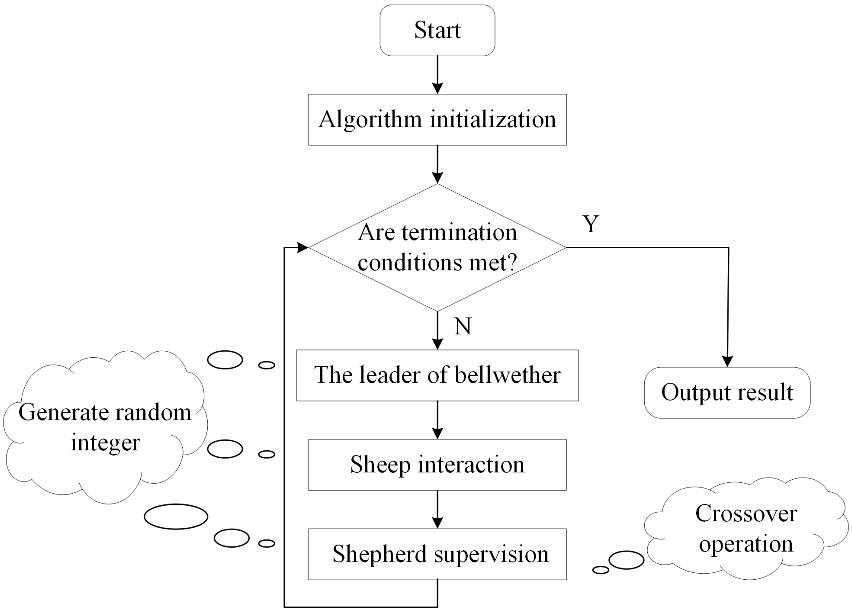


Figure 6. The flow chart of the discrete sheep algorithm

Table 2. Table of initial information of UAVs

UAV number	Coordinate/km	Endurance/km	Load capacity	Kill probability
1	$(1, 1, 0)$	110	2	0.9
2	$(1, 6, 0)$	120	2	0.9
3	$(4, 55, 0)$	150	3	0.8
4	$(1, 60, 0)$	150	2	0.8
5	$(1, 78, 0)$	100	1	0.7
6	$(2, 28, 0)$	120	1	0.8
7	$(10, 90, 0)$	150	1	0.6
8	$(12, 99, 0)$	130	1	0.9

Table 3. Table of initial information of targets

UAV number	Coordinate/km	Mission value	Load capacity
1	$(85, 10, 0)$	1.0	
2	$(65, 30, 0)$	0.75	$[2, 3]$
3	$(80, 60, 0)$	0.8	$[3, 6]$ $[3, 5]$
4	$(95, 95, 0)$	0.6	
5	$(90, 80, 0)$	0.7	
6	$(95, 50, 0)$	1.0	
7	$(50, 0, 0)$	1.0	$[7, 1]$
8	$(60, 88, 0)$	0.9	$[8, 5]$

For the problem of multi-UAVs collaborative global target allocation, the relative weight of each target can be determined according to the commander's decision intention. Different values reflect different decision preferences of the commander. This paper simulates the perspectives of two different commanders [16]: commander 1 sets the weighting factor to $c_1 = 0.6$, $c_2 = c_3 = 0.2$ in order to give priority to less fuel consumption; commander

Table 4. Table of damage probability of UAVs after attacking targets

Goal/UAV	1	2	3	4	5	6	7	8
1	0.1	0.2	0.2	0.6	0.5	0.4	0.5	0.6
2	0.6	0.4	0.1	0.5	0.2	0.2	0.3	0.2
3	0.2	0.1	0.3	0.6	0.5	0.2	0.1	0.4
4	0.4	0.2	0.2	0.3	0.2	0.2	0.4	0.1
5	0.6	0.4	0.2	0.3	0.2	0.2	0.4	0.1
6	0.2	0.1	0.2	0.6	0.5	0.3	0.1	0.4
7	0.6	0.5	0.3	0.1	0.3	0.35	0.6	0.1
8	0.7	0.5	0.4	0.1	0.3	0.35	0.6	0.1

2 sets the weighting factor to $c_1 = 0.2$, $c_2 = 0.6$, $c_3 = 0.2$ for safer. Due to the uncertainty of UAV number and target number in actual combat, this paper conducts simulation experiments for three different application scenarios [24], which is set as follows:

1) Scenario 1: $u = t$, UAVs $U_1 \sim U_6$ attack target points $T_1 \sim T_6$;
2) Scenario 2: $u > t$, UAVs $U_1 \sim U_8$ attack target points $T_1 \sim T_4$;
3) Scenario 3: $u < t$, UAVs $U_1 \sim U_4$ attack target points $T_1 \sim T_8$.

4.2. **Simulation result.** This paper simulates the allocation problem in different scenarios of two commanders, the specific allocation results of commander 1 are shown in Table 5, Table 6 and Table 7, and the results of commander 2 are shown in Table 8, Table 9 and Table 10.

Table 5. Targets allocation result of scenario 1, commander 1

UAV	1	2	3	4	5	6
Goal	T_2	T_5	T_1	T_3	T_4	T_6
Range (km)	70.2638	89.56	84.0952	79	95.5249	95.5667

Table 6. Targets allocation result of scenario 2, commander 1

UAV	1	2	3	4	5	6	7	8
Goal	T_1	T_2	T_1	T_3	T_3	T_2	T_4	T_4
Range (km)	84.4808	65.9242	84.0952	79	81.0247	63.0317	85.1469	83.0963

Table 7. Targets allocation result of scenario 3, commander 1

UAV	1	2	3	4
Goal	$T_2 \to T_6$	$T_8 \to T_4$	$T_7 \to T_1$	$T_3 \to T_5$
Range (km)	106.3193	100.6931	85.76653	101.3607

Tables 5-10 describe the task allocation scheme for different scenarios of the simulation of different commanders. The range of the table represents the distance that the UAV will fly to the assigned target, and the corresponding target sequence assigned to the UAV. The results in the tables indicate that sheep optimization can solve the multi-UAVs cooperative global target allocation problem under different quantitative relations and constraints, and can get reasonable results. Because the global target allocation problem requires high quality of solution, fast convergence speed and great stability, this paper compares the performance of the discrete sheep optimization with the original genetic algorithm.

TABLE 8. Targets allocation result of scenario 1, commander 2

UAV	1	2	3	4	5	6
Goal	T_2	T_4	T_1	T_3	T_5	T_6
Range (km)	70.2638	99.4032	84.0952	79	89.0225	95.5667

TABLE 9. Targets allocation result of scenario 2, commander 2

UAV	1	2	3	4	5	6	7	8
Goal	T_2	T_2	T_1	T_3	T_4	T_1	T_3	T_4
Range (km)	70.2638	65.9242	84.0952	79	95.5249	84.9294	76.1577	83.0963

TABLE 10. Targets allocation result of scenario 3, commander 2

UAV	1	2	3	4
Goal	$T_7 \to T_1$	$T_2 \to T_6$	$T_3 \to T_5$	$T_8 \to T_4$
Range (km)	85.41075	101.9797	118.0529	101.0001

4.3. **Performance analysis.** In order to verify the search efficiency of the sheep optimization in solving the global target allocation problem, this paper compares the performance of the discrete sheep optimization with the genetic algorithm. The same parameter of the two algorithms is set to the same value, the crossover probability $P_c = 0.9$ and mutation probability $P_m = 0.1$ in the genetic algorithm.

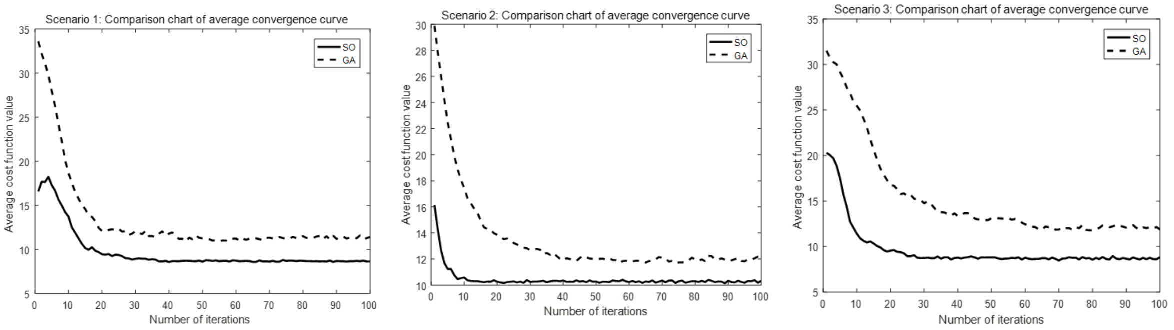
Taking scenario 1, commander 1 as an example, the average fitness function value of the initial population after population initialization is shown in Table 11. The cost function values of the initial population in different scenarios of commander 1 are stable: scenario 1 is about 33.7, scenario 2 is about 29.8, and scenario 3 is about 31.6. Table 9 shows that the cost function value of the first generation has no effect on the algorithm performance after 30 simulation experiments.

TABLE 11. Value of the average fitness function of the initial population in each scenario

Population initialization times (times)	30	100	500	1000
Scenario 1: Average cost function value	33.7014	33.7875	33.7575	33.7854
Scenario 2: Average cost function value	29.6725	29.8234	29.8156	29.8428
Scenario 3: Average cost function value	31.7752	31.5828	31.6724	31.6514

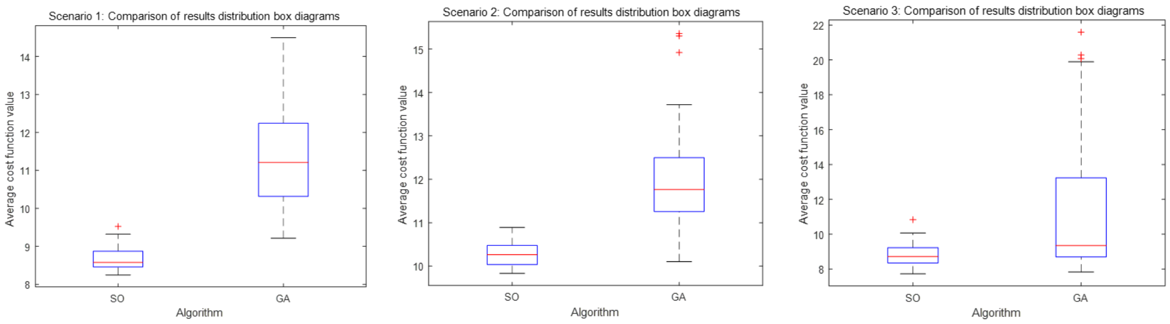
In order to avoid the influence of accidental factors in a single experiment, 30 simulation experiments were carried out for each scene of two commanders, the results were recorded, and then the average value was calculated. The comparison diagram of average convergence curve in different scenarios is shown in Figure 7 and Figure 9, and the distribution box diagram comparison of 30 test results in different scenarios is shown in Figure 8 and Figure 10.

Compared with the genetic algorithm, the discrete sheep optimization has a better average cost function value after the first population update, such as in the scenario 1 of commander 1, the SO is 16.57, the GA is 33.61, in the scenario 2 of commander 1, the SO is 16.14, the GA is 29.88, in the scenario 3 of commander 1, the SO is 20.29, the GA is 31.52. The results show that the discrete sheep optimization has the ability of fast global search. Figures 7-10 show that the discrete sheep optimization has faster convergence speed, better final solution quality and higher stability compared with the genetic algorithm. In addition, it has fewer parameters.



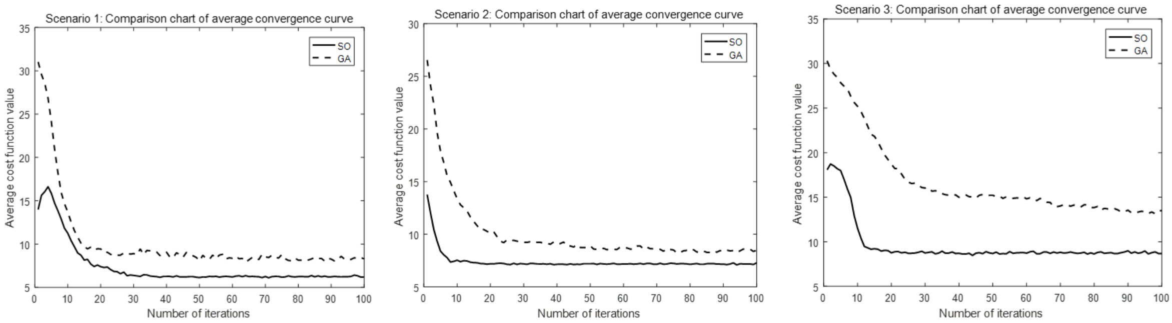
(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Figure 7. Comparison chart of average convergence curves in different scenarios of commander 1



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

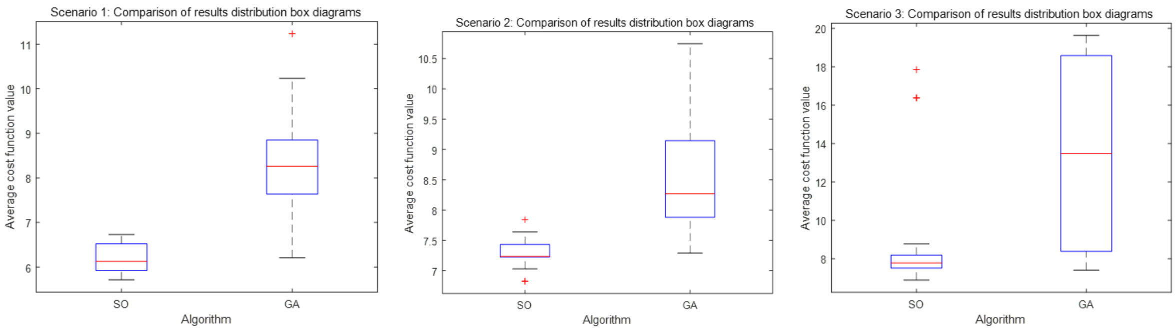
Figure 8. Comparison of test results distribution box diagrams in different scenarios of commander 1



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Figure 9. Comparison chart of average convergence curves in different scenarios of commander 2

The analysis results show that the convergence speed, solution quality and stability of the algorithm we proposed are obviously better than genetic algorithm. The algorithm has fewer parameters and can quickly converge in fewer iterations. It is stable near the optimal solution, and has the ability to jump out of the local optimal. Finally, it can better solve multi-UAVs cooperative global target allocation problem.



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

FIGURE 10. Comparison of test results distribution box diagrams in different scenarios of commander 2

5. **Conclusion.** In this paper, the complex multi-UAVs cooperative global target allocation problem is decomposed into several subproblems. Aiming at this problem, we establish a mathematical model of the typical quantitative relationship between UAVs and targets under the cost-profit index function and correlative constraints. The penalty function is used to deal with some constraint conditions to establish the fitness function, and the discrete sheep optimization is used to solve the problem. In simulation, the target allocation schemes in different application scenarios are obtained and compared with the genetic algorithm. The simulation results show that our algorithm can effectively solve the multi-UAVs cooperative global target allocation problem.

However, this paper only considers the target allocation problem with known target information. In the future research, the focus is to model the dynamic target allocation problem according to the unexpected situation that may be encountered in the navigation of UAV, and extend the application scenario of discrete sheep optimization to multi-target dynamic allocation.

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