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Research Article

A Decision-Making Method for Distributed Unmanned Aerial Vehicle Swarm considering Attack Constraints in the Cooperative Strike Phase

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In view of the growing military forces of various countries, unmanned aerial vehicle (UAV) swarms, as a new type of weapon, are gradually attracting the attention of more and more countries. Decision-making, as the core link in its application, has also become the focus of research in these countries. In this work, the distributed UAV swarm cooperative strike decision-making problems are separated from the distributed UAV swarm cooperative search strike decision-making problems, and the distributed UAV swarm cooperative strike multiobjective decision-making model is established, with the relevant constraints clarified. Besides, according to the analysis of the motion characteristics of UAV and the speed requirements of the distributed UAV swarm cooperative strike decision, an arc tangent trajectory planning method, conforming to the motion characteristics of UAV, is proposed. Moreover, a distributed cooperative strike decision-making method, based on the idea of "campaign endorsement and invitation cooperation," is put forward, with the effectiveness and superiority validated by simulation experiments.

1. Introduction

In recent decades, the unmanned swarm system combat technology comes into being, to cater for the rapid development of unmanned system technology, biological swarm intelligence technology, artificial intelligence technology, and wireless communication technology, as well as the ability requirements of attacking high-value targets, moving targets, time-sensitive targets, distributed targets, and other types of targets in the full depth of campaign tactics. Based on the distributed perception and computing and the autonomous networking and collaboration, unmanned aerial vehicle (UAV) swarm possesses the capacities of collaborative search, collaborative task perception, collaborative task decision-making, collaborative attack, and damage effect evaluation, thus greatly improving the cooperative fire fighting capability and comprehensive operational effectiveness and transforming the quantitative advantages into quality advantages. That attracts wide attention of all countries around the world. With the characteristics of decentralization and high autonomy, distributed UAV swarms can achieve the better combat effectiveness in large-scale combat, by contrast with the centralized UAV swarms [1, 2]. For the past few years, the in-depth researches on distributed UAV warm have been conducted by many experts in the world [3–5].

In terms of the control mode, the UAV swarms can be divided into centralized, distributed, and hybrid swarms. Therefore, the centralized and hybrid UAVs are applicable to the smaller UAV swarm operations. While, when using the two modes in the large-scale cluster operations, once the central UAV is destroyed, the entire swarm system shall lose its function. By comparison, when adopting the distributed UAV swarm, each UAV is in the same status, and the destruction of one UAV has little impact on the whole UAV swarm system. However, the great communication load of distributed UAV swarm may delay the response to the task or even reduce the standard for task execution. Therefore, in this work, a timely distributed cooperative strike method is proposed, directing at the decision-making problems of the distributed UAV bee swarm in the strike task execution, thereby

improving the combat effectiveness of the distributed UAV swarm and further providing some help for the cooperative operation of the future distributed UAV swarm.

In this work, it firstly extracts the problem of cooperative attack of distributed UAV swarms from the framework of the searching and attacking tasks performed by distributed UAV swarms and establishes a relevant model. Afterwards, based on the motion characteristics of UAVs and the relevant requirements for attacking task execution, the relevant constraints of the established model are clarified, and a three-dimensional path planning method is proposed for UAVs with attack speed constraints. Finally, a distributed cooperative strike decision method (DCSDM) is presented to solve this problem, and the effectiveness of the intermodel and the proposed method is verified by simulation, as well as the superiority of DCSDM.

The remainder of this work is structured as follows: in Section 2, the relevant researches on the multiagent collaborative decision-making method are discussed briefly. Then, the problems are described in Section 3, and our methods are presented in Section 4. The simulation research is given in Section 5, with the achieved results explored. Section 6 draws a conclusion with a summary and an outlook for the future work.

2. Related Work

The distributed UAV swarm is a kind of distributed multiagent system, and its attack decision problem can be deemed as a combination optimization problem of multiple UAVs to multiple objectives [2]. The key to solve this problem lies in the solution of the conflict between the local benefits of a single UAV and the overall benefits of the UAV swarm. Therefore, the conflict is caused by the information delay as a result of the distribution and decentralization of UAV swarm [6]. In view of the multiagent task decision-making problem in different scenarios, Luo et al. proposed a distributed task allocation algorithm in literature [7]. The algorithm can solve the problem of multiple task allocation of the distributed multirobots with the latest completion time, and this corresponds to the actual task scenario. Later, they also improved the traditional auction algorithm in literature [8] and presented a reasonable allocation mechanism to distribute the algorithm. Moreover, a model for joint search of multiple unmanned platforms is constructed in literature [9]. This model can satisfy the motion constraints of multiple UAV platforms and has obvious advantages in complex underwater missions with some practical meaning. To copy with the battlefield environment, two algorithms are proposed in literature [10], aiming at distributing the cluster weapons to multiple targets in a decentralized manner, exploring their hybrid algorithm, and verifying the superiority of the selected algorithm by simulation. In literature [11], UAV swarm attack/swarm defend adversarial decision-making is explored, by modeling each UAV as an independent intelligence, giving UAV the ability to make free decisions, and developing a distributed auction algorithm. Therefore, the algorithm allows each UAV to make decisions timely during the mission, with the effectiveness demonstrated by simulation experiments. Literature [12] presents a task-oriented task allocation framework based on auction algorithm, with good robustness in different tasks and environment demand scenarios. In literature [13], distributed task allocation and scheduling algorithms are put forward, aiming at tight coupling the tasks with time priorities. As for the possible conflict problem occurred during the flying of UAV swarms in airspace, it is suggested to set a safety interval and establish a cluster airspace conflict resolution method in literature [14], thereby effectively avoiding the occurrence of conflicts. In addition, different methods are described in literature [15–19], with the purpose of solving the route planning problem of UAV swarm, and good results are obtained. However, when performing the attack task in the actual attack scenario, the distributed UAV swarm sometimes needs to track the target and detonate and self-destruct at a high speed, thereby destroying the target [20, 21], while there are few academic research in this field currently.

3. Problem Description and Model Establishment

3.1. General Description of the Decision-Making Problem of Distributed UAV Swarm Cooperative Strike. As for the distributed UAV swarm cooperative attack, the decision-making is an important link to realize target allocation, task scheduling, timing coordination, route planning, conflict resolution, and other functions. Its connotation can be described as follows: "Each UAV in the swarms develops the own appropriate target and task based on the real-time situation, and determines the flight route from the starting position to the target position. By the inter aircraft communication with a certain frequency, it can select the route with the minimum (smallest) track cost, while ensuring the minimum (smallest) sum of track costs of all UAVs in the hive, and avoiding the collisions between UAVs" [3]. The decision framework presented in Figure 1 describes the typical search and strike tasks performed by the distributed UAV swarms. The global UAV decision benefits (also known as "global benefits") is the sum of local benefits, obtained by each UAV when executing corresponding decisions. Thus, the global decision benefits depend on the decision information and planning benefits. The decision variables merely include the matching information between the target and the UAV, and the planning income is the net income corresponding to the decision results. As for UAVs, the factors, affecting this income, include but are not limited to fuel consumption, target value, UAV location, and target location.

Usually, the decision-making problem of distributed UAV swarm cooperative attack can be described as N_u UAVs decision-making, and plan independently to attack N_t targets on the ground synergistically, thereby obtaining the maximum (largest) global benefit, with the following mathematical equation given:

$$\begin{aligned} &\max_{\{f_{ij}\}} \sum a_{ij}\left(f_{ij}, \theta_{ij}\right), \\ &\text{s.t.} f_{ij} \in \{0, 1\}, \\ &C\left(f_{ij}, \theta_{ij}\right) \le b, \end{aligned} \tag{1}$$

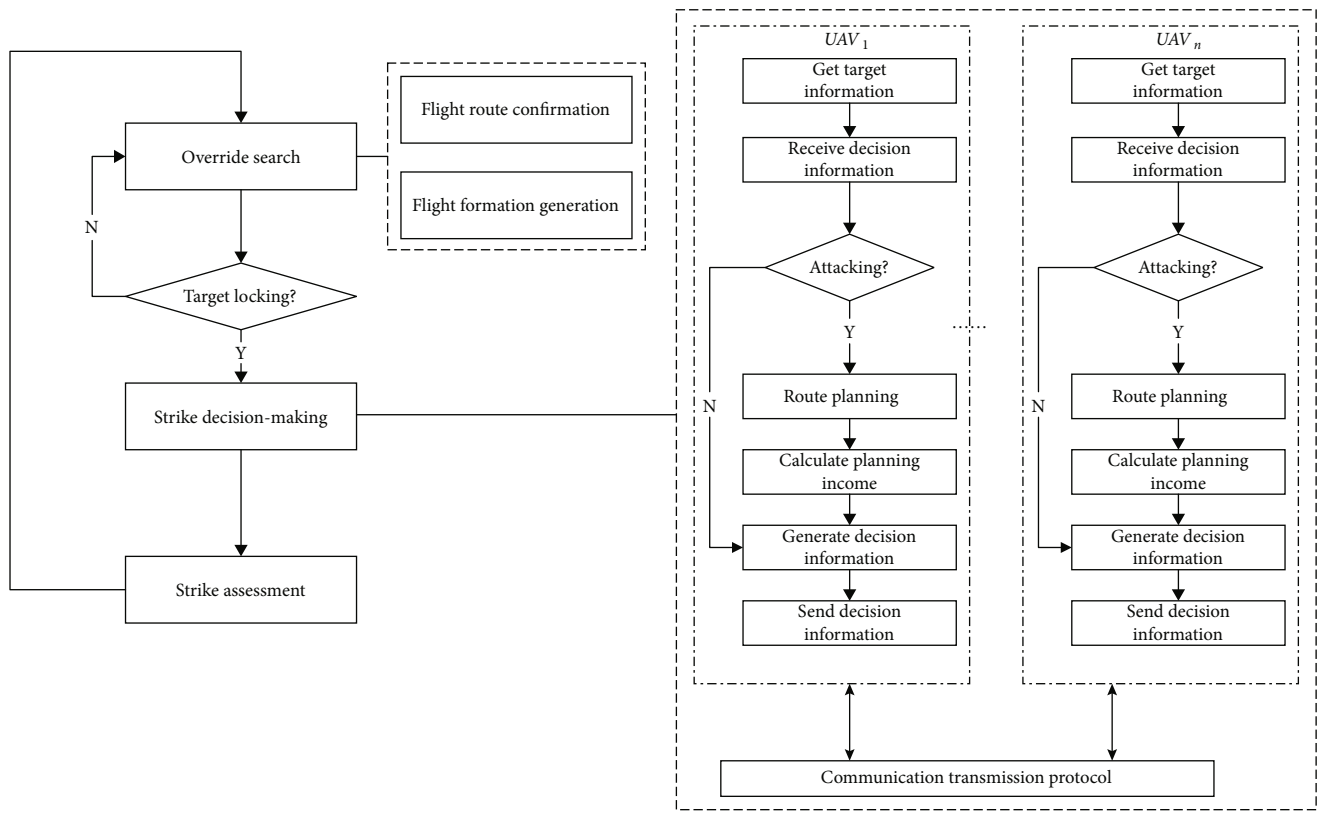


Figure 1: Decision framework of distributed UAV swarm for the execution of cooperative search and attack tasks. As for the strike task execution of UAV swarm, the prerequisite is to obtain the information of the target to be struck, and this requires override search. Once determining to attack the target, each UAV shall make a decision on the target and judge whether the target is worth attacking by conducting a series of assessments.

where $i \in I = \{1, \cdots, N_u\}$ and $j \in J = \{1, \cdots, N_t\}$. f_{ij} refers to the decision information matrix, satisfying $f_{ij} \in \{0, 1\}$. $f_{ij} = 1$ means that UAV_i is allocated to attack T_j, otherwise else. θ_{ij} represents a set including variables that may affect the benefits of UAV_i striking T_j. a_{ij} represents the net income of UAV_i attacking T_j, when f_{ij} and θ_{ij} are determined. $C(f_{ij}, \theta_{ij}) \leq b$ indicates the constraints that the decision result needs to meet, mainly including the distributed control constraint, load constraint, and dynamic constraint of UAV swarm.

The three variables, a_{ij}, f_{ij}, and θ_{ij}, are interdependent, similar to the multiple traveling salesman problem (MTSP). This internal coupling relationship makes it more difficult to solve the problem effectively [4]. Also, the numerous UAVs make it easy to increase the dimensions of the solutions, making the problem facing the "dimensional disaster."

Simultaneously, when UAV swarms perform tasks, the attacking order is different as for the different targets. For example, as for the different time, the order of targets discovery determines the attacking order of UAV swarms. While, as for the same time, if the strike tasks are needed when facing multiple targets, the attacking order of UAV swarms can be affected by the importance of different targets. Besides, the time, required by the UAV swarm to execute the strike task against different targets, is also different. Before the UAV swarm executes the strike task against the next target, the strike effect of the previous target needs to be evaluated firstly. Only when the evaluation results meet the requirements, the next task can be executed. Otherwise, "restrike" shall be needed.

Therefore, the value of decision-making income is closely related to the time, and Equation (1) is given as follows:

$$\begin{aligned} &\max_{\{f_{ij}\}} \sum a_{ij}\left(f_{ij}, \theta_{ij}, \tau_{ij}, t_{ij}\right), \\ &\text{s.t.} f_{ij} \in \{0, 1\}, \\ &C\left(f_{ij}, \theta_{ij}\right) \leq b, \end{aligned} \tag{2}$$

where T_{ij} and t_{ij} are the target strike time and target strike duration matrix corresponding to the decision-making information matrix $\{f_{ij}\}$. Namely, T_{ij} is the time when UAV_i attacks T_j and t_{ij} is the time required for UAV_i attacking T_j. When $f_{ij} = 0$, T_{ij} and t_{ij} are the default quantities.

3.2. Definite Constraint Conditions and Model Establishment. As the decision-making problem represented by Equation (2) is universal and difficult to solve, the

constraints of the problem can be defined to simplify the problem.

Constraint 1 refers to the target damage constraint. That is, the UAV assigned to the target T_j can meet the conditions required by complete damage of the target. The examples are as follows:

(1) Quantitative condition: due to the limitation of load carried by UAV, it is difficult for a single UAV to damage a target completely, so it is necessary to win by quantity. When supposing that the number of UAVs required to complete the target damage T_j is N_j, the constraint can be described as follows:

$$\sum_{i=1}^{N_u} f_{ij} \geq N_j, \quad \forall j = 1, \cdots, N_t \tag{3}$$

(2) Detonation constraint: to ensure the effectiveness of UAV strike, the load carried is usually triggered for detonation. That is, when the UAV hits the target, the speed is high enough to cause detonation. The speed can be defined as a multiple of the initial speed, and the constraint condition can be depicted as follows:

$$v_T \geq b^* v_0, \tag{4}$$

where v_T refers to the speed when the UAV reaches the target position and b is a constant

Constraint 2 refers to the uniqueness of UAV hitting target. Namely, each UAV can only hit one target, followed by self-destruction after hitting. As the UAV swarm wins the victory by virtue of the number advantage and has a high-cost performance ratio, the UAV in the swarm is set as a small UAV with limited carrying load in this work, without recycle after hitting. This constraint is given as follows:

$$\sum_{j=1}^{N_t} f_{ij} = 1, \quad \forall i = 1, \cdots, N_u. \tag{5}$$

Constraint 3 refers to the time consistency constraint. That is, UAVs assigned to the same target need to reach the target position at the same time, thus achieving the maximum strike effect. This constraint can be described as follows:

$$\tau_{kj} = \text{constant}, \quad \forall k, j : f_{kj} = 1. \tag{6}$$

Constraint 4 refers to the target attack order. Namely, if the number of UAVs is insufficient after detecting the targets at the same time, priority should be given to the target with high value. This constraint is depicted as follows:

$$\begin{gathered} \tau_{\cdot j_1} < \tau_{\cdot j_2}, \quad \text{if } a_{\cdot j_1} > a_{\cdot j_2}, \\ \text{s.t.} \sum_{j=1}^{N_t} N_j > N_u. \end{gathered} \tag{7}$$

Constraint 5 refers to the UAV kinematic constraint, that is, the flight path when the UAV goes forward to perform the strike task, conforming to the kinematic characteristics of the UAV. Considering the large number of UAVs in the swarm, when the six-dimensional particle model is used to model each UAV, the computational complexity shall be greatly increased, and the computational time shall be long; thus, timely response can not be given to the needs of the battlefield. By referring to the aircraft kinematic model proposed in the relevant research [5], Equation (8) is adopted in this work, aiming at describing the motion of UAV in the three-dimensional space.

$$\begin{gathered} p_i(t) = \begin{bmatrix} x_i(t) \\ y_i(t) \\ z_i(t) \end{bmatrix}, \\ \dot{p}_i(t) = \begin{bmatrix} v_i(t) \cos \gamma_i(t) \cos \phi_i(t) \\ v_i(t) \cos \gamma_i(t) \sin \phi_i(t) \\ v_i(t) \sin \gamma_i(t) \end{bmatrix}^T, \\ \dot{\gamma}_i(t) = \mu_i(t), \\ \dot{\phi}_i(t) = \omega_i(t), \\ \dot{v}_i(t) = a_i(t), \\ \mu_i(t) \in \left[-\mu^i_{\max}, \mu^i_{\max}\right], \\ \omega_i(t) \in \left[-\omega^i_{\max}, \omega^i_{\max}\right], \\ a_i(t) \in (a^n_{\max}, a^p_{\max}), \\ 0 < \phi_i(t) < 2\pi, \\ -\frac{\pi}{2} < \gamma_i(t) \leq \frac{\pi}{2}, \end{gathered} \tag{8}$$

where $p_i(t)$ represents the position of UAV_i, $\dot{p}_i(t)$ refers to the displacement change rate of UAV_i, $v_i(t)$ is the speed of UAV_i relative to the geodetic coordinate system, $r_i(t)$ refers to the angle of pitch of UAV_i, $\mu_i(t)$ is the pitch angle change rate, $\varnothing_i(t)$ is the heading angle of UAV_i, $w_i(t)$ is the change rate of heading angle, and $a_i(t)$ is the acceleration of UAV_i. The above variables are instantaneous variables at the time *. Simultaneously, to ensure the more stable UAV flight, the performance parameters of the UAV are limited to a certain range. Due to the different acceleration and deceleration controllers of UAV and the correlation of the overload capacity of UAV with the current speed, the maximum acceleration and deceleration of UAV depend on the current state of UAV, with the following requirements satisfied:

$$|a^n_{\max}| < |a^p_{\max}|. \tag{9}$$

When UAV strikes the ground target, it needs to change the original course, fly to the target position, and adjust the speed, thereby meeting Equation (4). To ensure the stability of UAV navigation with their heading and speed not adjusted simultaneously, Chen et al. [22] firstly proved that there is a smooth shortest path between two points that meets the constraint of aircraft turning radius. Therefore, the turning radius of UAV refers to the minimum turning radius, namely, Dubins path. As demonstrated by Dr. Yang Jian, when UAV uses the Dubins curve in planning the UAV trajectory, the speed can be adjusted according to the maximum angular rate and direction of the UAV, thus obtaining the maximum traceable angle [5]. Then, there can be an acceleration in a straight line along the maximum tracking angle. However, with this method, the course adjustment time of UAV is increased, and the acceleration time of UAV is reduced. While when the UAV needs to strike a target, the speed of UAV approaching the target is required merely, and there is no high requirement for speed direction. Thus, the arc tangent trajectory planning method is proposed in this work. That is, the UAV changes the navigation direction with the minimum turning radius and then travels in a straight line towards the direction of the target, till to reach the target.

The motion of UAV in three-dimensional space can be decomposed into the horizontal plane and the vertical plane. The minimum turning radiuses of UAV in horizontal direction and numerical direction are determined by Equation (10), where $\vartheta^i_{\max}$ refers to the maximum roll angle, n represents the overload factor, and g is the gravitational acceleration.

$$R^{\min}_{i,h} = \frac{v_i^2 \cos^2 \gamma^i_{\max}}{ng \sin \left|\vartheta^i_{\max}\right|},$$
$$R^{\min}_{i,v} = \frac{v_i^2}{g\left(n_f\text{-}\cos\left(\gamma_i\right)\right)}. \tag{10}$$

Now, by taking the adjustment in the horizontal plane as an example, the motion of the UAV can be explored. As exhibited in Figure 2, the UAV travels along the OD direction, from the initial position of point O to the target position of point B ($\overset{\frown}{OEF}$ and red dotted-line FB refer to the trajectory of UAV, by only considering the motion direction with the method described in [5]. $\overset{\frown}{OA}$ and dotted line AB represent the trajectory obtained, by adopting the arc tangent trajectory planning method.) First, the direction of the arc OA segment is adjusted with the minimum turning radius, and then, AB segment is accelerated along the straight line with the maximum acceleration $a^p_{\max}$, till to reach the speed $b \cdot v_i$. The red-dotted line refers to the navigation path adjusted by applying the Dubins path. The speed positions of the two methods are presented in Figure 3.

Generally, the decision-making problem of distributed UAV swarm cooperative attack can be described as N_u UAVs decision-making.

As observed from Figures 2 and 3, the planned track, applying the Dubins curve application method, greatly

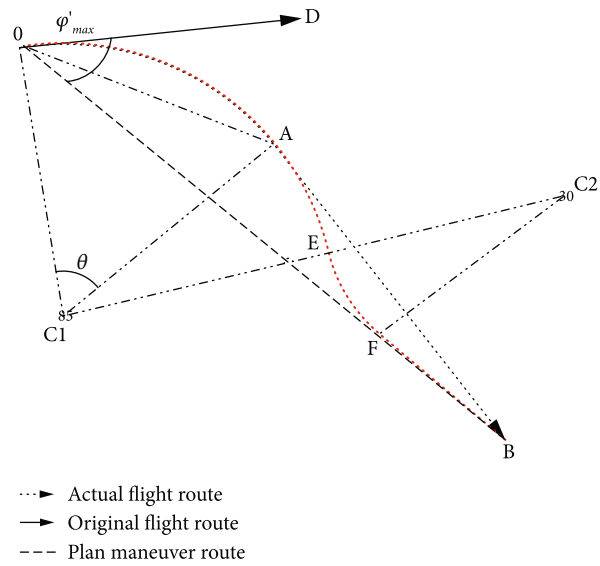


Figure 2: UAV flight route design. $\overrightarrow{OD}$ refers to the speed direction of UAV. C1 and C2 are centers of the two circles with the minimum turning radiuses.

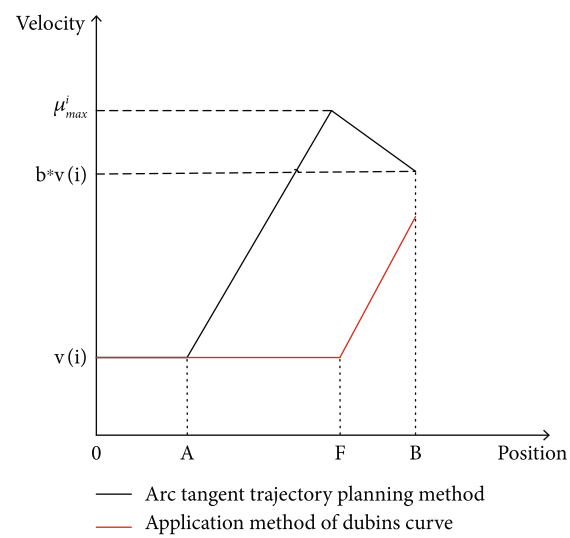


Figure 3: Speed position curve.

shortens the linear acceleration time of UAV, thus making it difficult for UAV to meet the speed requirements as presented in Equation (4) when reaching the target position. By adopting the arc tangent track planning method, not only the requirements of Equation (4) but also those of Equation (6) can all be satisfied. As for the UAV swarm assigned to the same target, it needs to take the minimum ideal time $\text{time}_{\min}$ as the time that is required to reach the target with the maximum acceleration when adopting the arc tangent path planning method. Besides, it is required to find the maximum one time_j from all $\text{time}_{\min}$, determine the UAVs with the decision of attacking T_j, and adjust the speed, till to reach the flight time time_j. Meanwhile, it can be deemed that the UAV meets the requirements of Equations (4) and (6).

The maximum yaw angle $'\varphi_{\max}$ of striking target of arc tangent trajectory planning method is required. That is, there is a maximum angle $'\varphi_{\max}$ between the planned maneuver route of UAV and the original flight route of UAV. This can ensure that when planning the route with the minimum turning radius and the maximum acceleration, the speed of UAV can meet the requirements at the time of reaching the target position. The solution process is as follows:

The distance between points O and B is supposed as D_{ij}. As UAV_i starts to adjust the motion direction by taking C1 as the center at the starting time, the coordinate of the initial position O of UAV is set as (x_i, y_i), and the position coordinate of C1 can be obtained based on the motion direction of UAV_i.

$$\mathrm{C1}: \left(x_i + \cos\left(\phi_i + \frac{\pi}{2}\right) r^i_{\min}, y_i + \sin\left(\phi_i + \frac{\pi}{2}\right) r^i_{\min}\right). \quad (11)$$

According to the motion angle of UAV_i, the coordinate equation of point A can be obtained with the equation below.

$$A: \left(x_i + r^i_{\min}(\sin(\theta + \phi_i) - \sin\phi_i), y_i - r^i_{\min}(\cos(\theta + \phi_i) - \cos\phi_i)\right). \quad (12)$$

The shortest distance between points A and B can be observed from the following kinematic equation.

$$|\mathrm{AB}| = \frac{\left(b^2 - 1\right) * v_i}{2^* a^p_{\max}}. \quad (13)$$

Because $\angle\mathrm{OAC1} = (\pi - \theta)/2$, then $\angle\mathrm{OAB} = \pi - \theta/2$. In $\measuredangle\mathrm{OAB}$, the lengths of $|\mathrm{OB}|$ and $|\mathrm{AB}|$ are known, and $|\mathrm{OA}|$ can be expressed as a function about θ with the coordinates of points A and O. According to the cosine theorem, this function is combined with the equation below.

$$\cos\angle\mathrm{OAB} = \cos\left(\pi - \frac{\theta}{2}\right) = -\cos\frac{\theta}{2}. \quad (14)$$

Thus, the simultaneous equation can be transformed into a linear equation with one variable. Theoretically, the value of radical solution θ can be obtained. Therefore, the cosine value of $\angle\mathrm{AOB}$ can be obtained as follows:

$$\begin{aligned}\cos\angle\mathrm{AOB} &= \frac{|\mathrm{OA}|^2 + |\mathrm{OB}|^2 - |\mathrm{AB}|^2}{2^*|\mathrm{OA}| * |\mathrm{OB}|} \\ &= \frac{\left|2^* r^i_{\min}{}^* \sin\theta\right|^2 + D_{ij}{}^2 - \left|\left(\left(b^2 - 1\right) * v_i\right)/\left(2^* a^p_{\max}\right)\right|^2}{2^*\left|2^* r^i_{\min}{}^* \sin\theta\right| * D_{ij}}.\end{aligned} \quad (15)$$

Then, $'\varphi_{\max} = \angle\mathrm{AOB} + \angle\mathrm{AOD} = \arccos\angle\mathrm{AOB} + (\theta/2)$ is obtained. Therefore, when the position of target T_j deviates from the heading angle φ_{ij} of UAV (UAV_i), it deems that the UAV can strike the target.

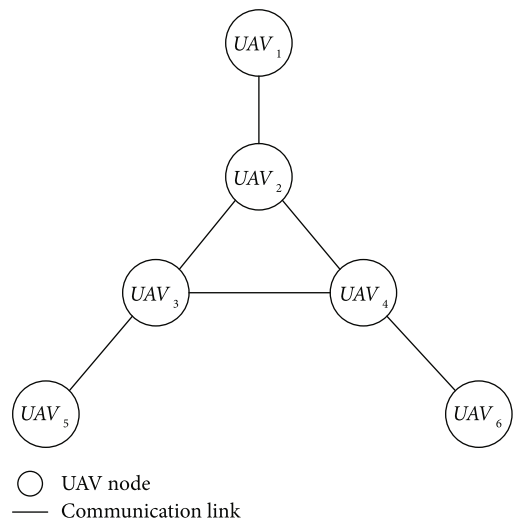


Figure 4: Small distributed UAV swarm A.

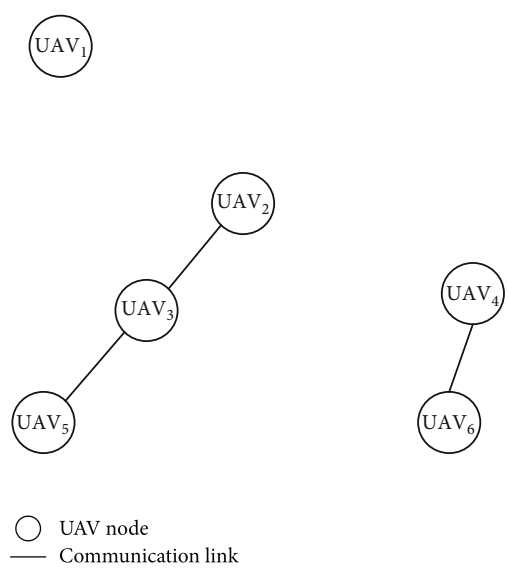


Figure 5: Small distributed UAV swarm B.

$$\left|\varphi_{ij}\right| \leq' \varphi_{\max}. \quad (16)$$

Similarly, in the vertical direction, the constraint on the pitch angle of the striking target can be satisfied.

$$\left|\delta_{ij}\right| \leq' \delta_{\max}. \quad (17)$$

In brief, the model of the decision-making problem of the distributed UAV bee swarm cooperative attack, sometimes, can be established as follows:

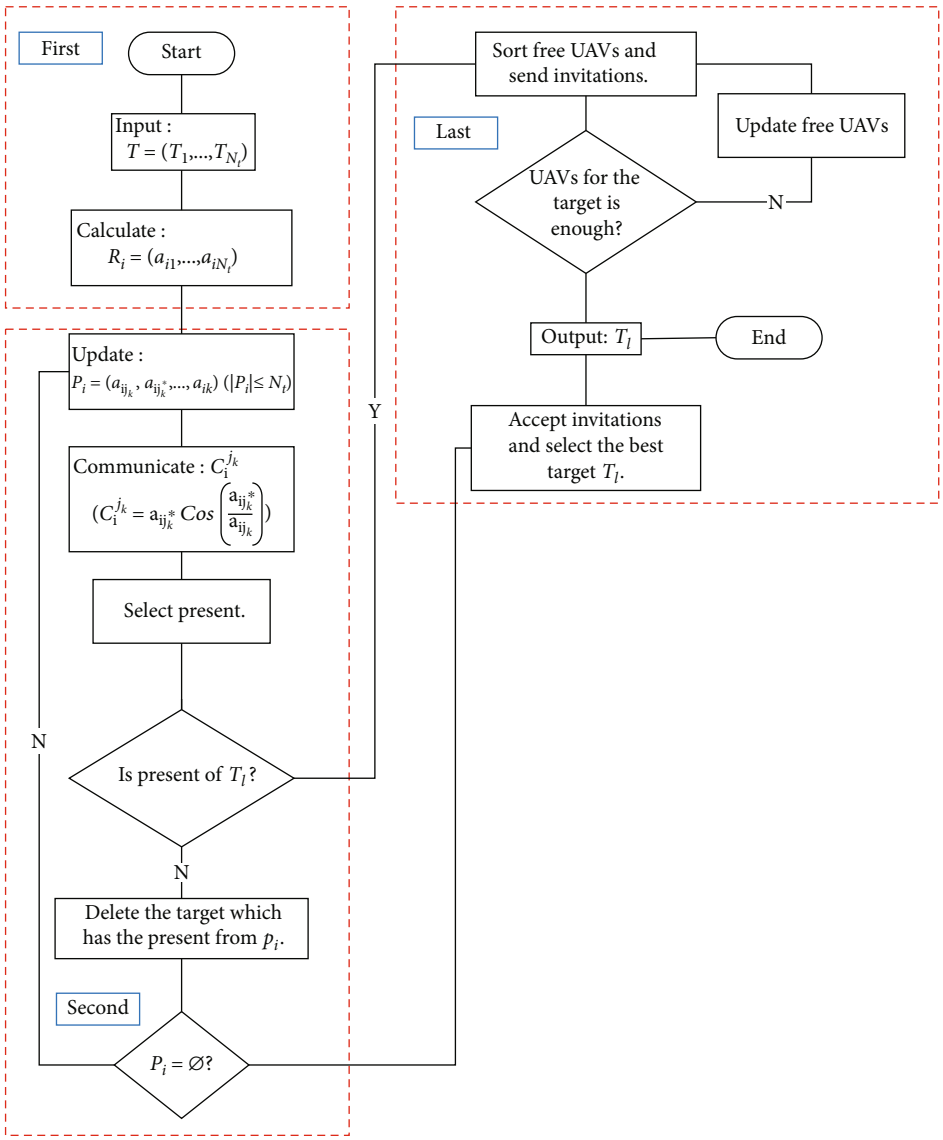


Figure 6: Decision flow chart of single UAV. Each UAV shall complete this decision flow chart after acquiring target detection information, thereby ensuring the distribution of UAV swarms.

$$\begin{aligned}
&\max_{\{f_{ij}\}} \sum_{i=1}^{N_u}\left(\sum_{j=1}^{N_t} a_{ij} f_{ij} A_{ij}\right),\\
&\text{s.t.} \sum_{i=1}^{N_u} f_{ij} \ge N_j, \quad \forall j = 1,\cdots,N_t\\
&\sum_{j=1}^{N_y} f_{ij} = 1, \quad \forall j = 1,\cdots,N_u\\
&A_{ij} = \begin{cases} 1, & \left|\varphi_{ij}\right| \le \varphi_{\max} \text{ and } \left|\delta_{ij}\right| \le \delta_{\max},\\ 0, & \text{others},\end{cases}\\
&f_{ij} \in \{0,1\}.
\end{aligned} \tag{18}$$

As for the equation above, A_{ij} refers to the angle decision variable, with value of 1 when UAV meets the constraints of Equations (16) and (17). This means that UAV_i can attack T_j. The objective function is to maximize the global benefit at a certain time. Thus, once obtaining the decision result, constraint 4 shall also be satisfied. Meanwhile, in view of the several objectives, such as the closest flight distance and the trajectory satisfying the kinematic characteristics of UAV, the constraints can also be met.

4. Online DCSDM

4.1. Distributed Structure Description Based on Graph Theory. As there is no central node in the distributed UAV swarm, and each UAV has the same position in the swarm, the final decision result of the swarm completely depends on the decision-making ability of each UAV, as well as the cooperation between UAVs. This cooperation is mutual and has no directionality. Thus, an undirected graph can be used in describing the distributed structure of UAV bees.

Therefore, * refers to the vertex sets, representing UAVs, while * refers to edge sets, delegating the communication links between UAVs. There is also the cooperation information flow between UAVs. Besides, each undirected graph can be represented by the expected corresponding adjacency matrix.

Figures 4 and 5 exhibit the two small distributed UAV clusters composed of six UAVs, respectively, represented by adjacency matrixes

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \end{bmatrix},$$
$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \end{bmatrix}, \quad (19)$$

respectively, where $(A/B)_{ij} = 1$ indicates that there is a communication link between UAV_i and UAV_j, with information transferred directly. Otherwise, the information can not be transferred directly. However, if information can be transferred indirectly by virtue of other UAVs, the UAV hive is deemed to be distributed. As observed, the small distributed UAV swarm A is a distributed Unicom UAV swarm, while the small distributed UAV swarm B is not a distributed Unicom UAV swarm. In this work, the UAV swarm explored is set as a distributed Unicom UAV swarm.

4.2. DCSDM. In the distributed UAV swarm system, each UAV is an independent individual, tending to attack the target that can maximize its benefits when making decisions. However, in view of the swarm as a whole, this decision-making method is likely to cause the situation, where there are a large number of UAVs allocated to one target while insufficient number of UAVs allocated to another target, thus causing the resource mismatch. Hence, to balance the profit relationship between UAV individuals and UAV swarm as a whole, the method of selecting the "spokesperson" for each target is proposed, by comparing with the competitiveness of different UAVs for different targets. The "spokesperson" will judge the rationality of the number of UAVs allocated to the current target, thereby achieving the decision of coordinated attack on ground targets by UAV bees with connectivity. For example, if the number of UAVs exceeds the number needed by the target, and all the UAVs have the same competitiveness against the same target, rules

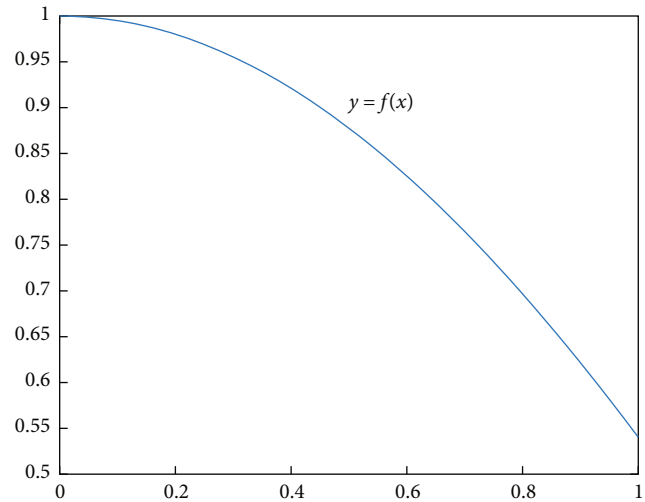


Figure 7: Competitiveness function. The function is monotonically decreasing, and the value of y can also be taken as [0,1], when $x \in [0, 1]$. Thus, it meets the condition of being a competitive function. This function is not unique and can be changed according to the actual needs.

Table 1: Parameter settings related to decision space.

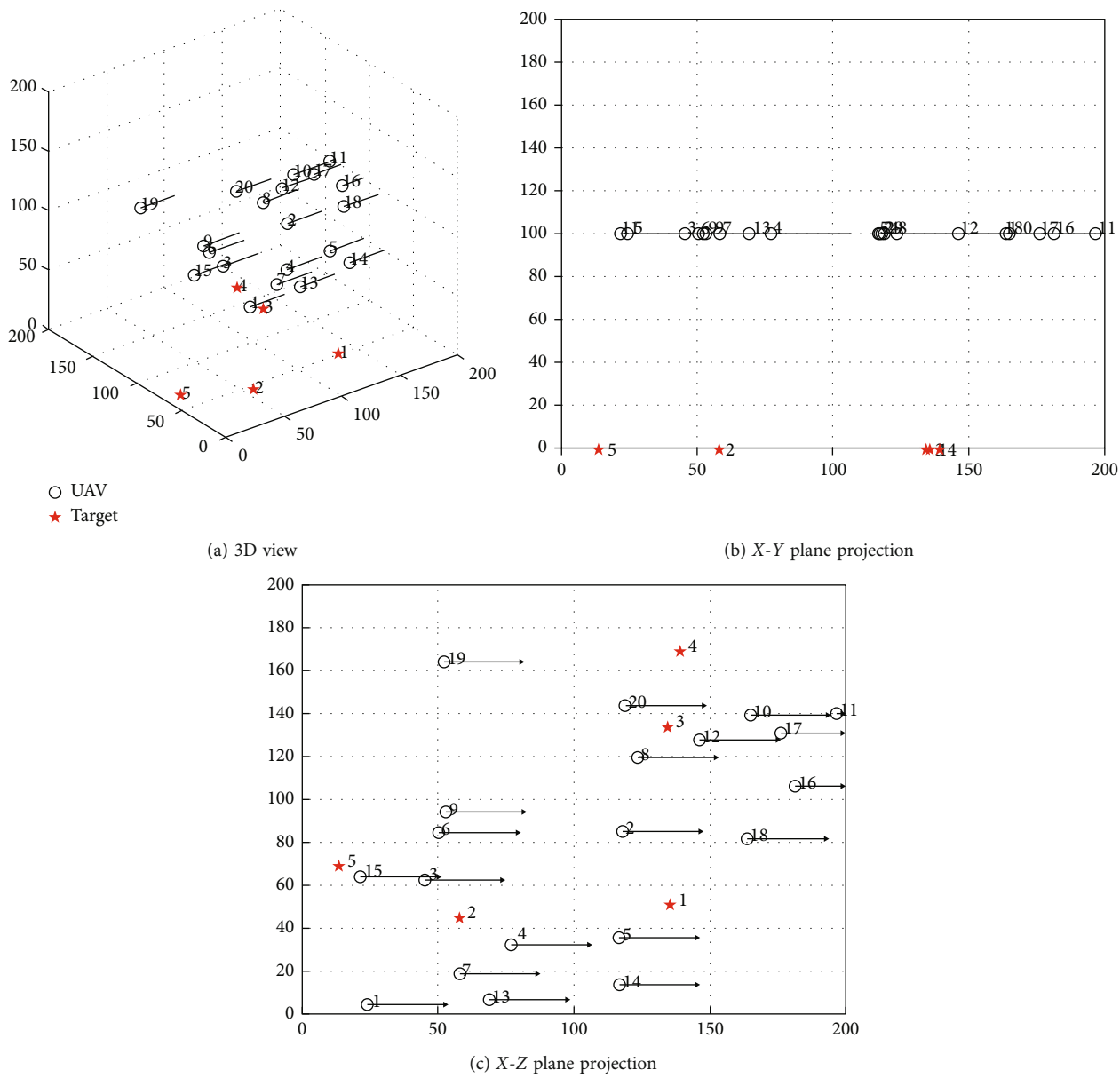
Target type	Target number	Coordinates (m)	Target damage income	Required UAV number/N_j
A	1	(70, 110, 0)	200	2
A	2	(110, 61, 0)	200	2
B	3	(160, 198, 0)	100	1
A	4	(23, 177, 0)	200	2
B	5	(139, 117, 0)	100	1

Table 2: UAV swarm status parameters.

Number	Velocity (m/s)	Yaw angle (rad)	Pitch angle (rad)	Angular velocity (rad/s)	Acceleration range (m/s^2)
20	10	$\pi/2$	0	1.1	(5,10)

can be formulated to resolve the conflict. The decision-making process of a single UAV is conducted, according to the flow chart exhibited in Figure 6.

By taking UAV_i as an example, the whole decision process can be illustrated for a single UAV. The first step is the information update. The UAV_i receives and filters the target information, leaving only those targets having been reconnoitered, but not struck or not completely struck, and needing to be hit incompletely. Also, the set of strikable targets is constructed, and these targets are evaluated simultaneously, thereby obtaining the net gain $R_i = (a_{i1}, \cdots, a_{\mathrm{iN}_t})$ that can be obtained by striking each target and storing this net gain set with the set of strikable targets. The second step is to compete for "advocates." Therefore, the "advocate" is a virtual assignor of each target, and there are two conditions for advocate selection of a target: (1) UAV_i is determined to attack the target and (2) UAV_i is the most or more



(a) 3D view

(b) X-Y plane projection

(c) X-Z plane projection

Figure 8: Real time position map of UAV swarm. "→" refers to the speed direction of UAV. The UAV flight direction is consistent during the coverage search.

competitive for the target. As believed, every drone tends to be a "spokesperson," so every drone needs to compete for a "spokesperson." When UAV_i competes for the "spokesperson," it needs first to identify the target with the largest net gain in the target set (numbered j_k), as well as the target with the next largest net gain (numbered j_k^*). Then, the competitiveness $C_i^{j_k}$ of UAV_i against the target T_{jk} is calculated according to Equation (20), and it is transmitted as competitiveness information to other UAVs, by applying the communication transmission protocol presented in Figure 1. Also, the competitiveness information $C_p^{j_q}$ is received from other UAVs. Meanwhile, UAV_i shall be calculated and compared with the competitive information of all drones. As for each target, the most competitive UAV needs to be selected and marked as the "spokesperson" of that target. Besides, it is required to judge whether UAV_i becomes the "spokesperson" of target T_{jk}. If yes, the condition, whether all the "spokespersons" of all targets have competed for the result, needs to be judged, so as to start the next step. Otherwise, UAV_i shall select the target $T_{j_k^*}$ to participate in the next competition for the "spokesperson," until all the "spokespersons" of all targets have competed for the result. In this step, there are only two results for the role of each drone, becoming a "spokesperson" or not becoming a "spokesperson." Moreover, as each drone obtains information about the target before competition, each drone may obtain its own role eventually. The limited nature of the target also ensures the feasibility of this step and the achievement of the final result, without getting stuck in a dead-end

cycle. The third step is to start or accept an invitation to collaborate. If UAV_i becomes the "spokesperson" of a target in the second step, it will send invitations to the drones of its representing target, based on the number of drones required by the completion of the fight against that target. In addition, it can choose the drones from the highest to the lowest, according to the competitiveness of other drones against that target. If UAV_i does not become a "spokesperson," it will choose from the invitations received and accept the "spokesperson" drone of the target of maximizing its net benefit.

By combining Figures 1 and 6, it can be known that there are only two final positions of each UAV in the whole decision process, attacking a certain target or not attacking the target. Moreover, the information of our set target is known and limited in number, so the final state of the UAV can be determined with the distributed attack decision method, with feasibility of the method guaranteed.

$$C_i^{j_k} = a_{ij_k}{}^* f(x),$$
$$x = \frac{a_{ij_k^*}}{a_{ij_k}}. \tag{20}$$

The following points need to be explained:

(1) Since every UAV tends to attack the target of maximizing its own net income, our ultimate goal is to find a decision result, thus maximizing the overall net income. This may cause the target of some UAVs to be not the target with the largest net income, but the target with the second largest net income, or even the target with lower net income. Thus, to balance the relationship between the local benefits of a single UAV and the overall benefits of the UAV swarm, the concept of the competitiveness of the UAV against the target is proposed. From a local perspective, the higher the net income of the target, the greater the competitiveness of the UAV. From a global perspective, if two UAVs have the same net income for the same optimal target and the different net incomes for the sub optimal target, the final decision shall obviously be the UAV with higher net income for the suboptimal target, after by making a concession. Therefore, the net income for the suboptimal target will affect the competitiveness of the optimal target in the global decision-making. That is, the closer the net income for the suboptimal target is to the net income for the optimal target, the smaller the competitiveness of the UAV against the optimal target. Besides, it needs to be understood that the competitiveness of the UAV against the target shall not be less than 0. As a result, the competitiveness calculation formula is presented as shown in Equation (20). x refers to the competition influence factor, the ratio of the suboptimal target net income value to the optimal target net income value, with the value range of [0,1]. Based on the above analysis, the competitiveness function $f(x)$ should meet the conditions as below. The function decreases monotonically within [0,1], and the value range is $[\varepsilon,1]$, where ε is a decimal to limit the minimum value of competitiveness. $f(x) = \cos x$ is selected to meet the requirements. The competitiveness function image is exhibited in Figure 7

Table 3: Decision results.

Target number	UAV number
1	5, 7, 14
2	1, 15
3	18
4	9, 20
5	2, 8

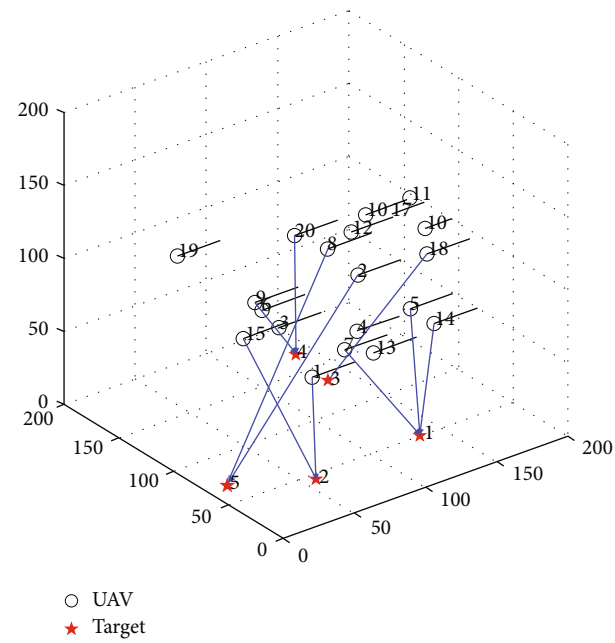


Figure 9: Schematic diagram of decision results. The UAV will attack the corresponding target in the direction indicated by the blue arrow. The blue line indicates the assignment of the UAV to the corresponding target.

Table 4: Parameters of normal PSO.

Initial population	Number of algorithm iterations (algorithm termination condition)	Inertia weight	Social weight	Cognitive weight
500	1000	1.1	1.5	1.5

Table 5: Parameters of improved PSO.

Initial population	Number of algorithm iterations (algorithm termination condition)	Inertia weight	Social weight	Cognitive weight	Inertial weight damping ratio
500	1000	1.1	1.5	1.5	0.98

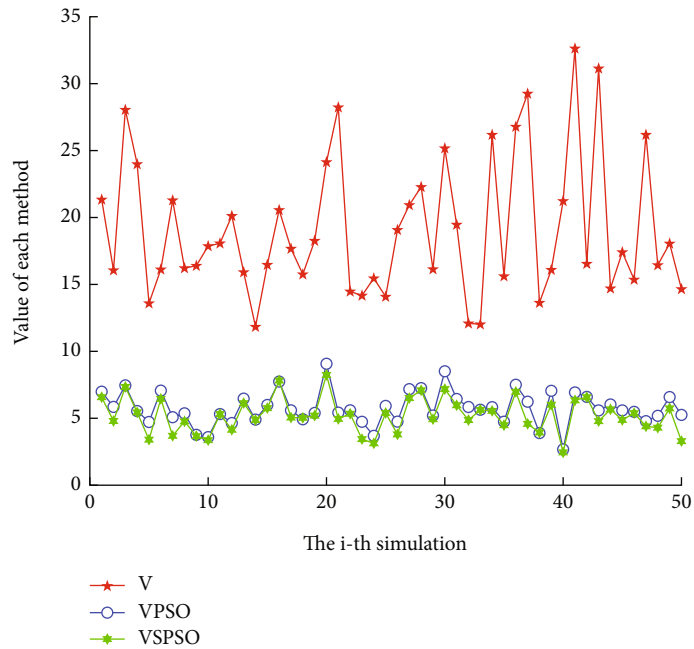


Figure 10: Value chart of decision results for that 20 UAVs which cooperate to strike 10 targets.

(2) "Spokesman" UAV_i shall send invitation messages to target T_j to $(N_j - 1)$ UAVs, excepting the own UAV. Meanwhile, there may be a conflict. Namely, there are two or more UAVs with the same competitiveness to the target, and they are ranked $(N_j - 1)$ in the competitiveness ranking of target T_j. By sending invitations to all these UAVs, UAV resources can be dislocated. Thus, the number of UAVs attacking one target may exceed the required number, while that attacking another target shall be insufficient. Hence, it needs to select one of the UAVs for invitation, and to invite other UAVs, this invitation should have been rejected. This selection can be given by adopting the method of sequencing. Namely, all UAVs are numbered according to the old and new degree, delivery time, or other information, before leaving the airport. The smaller the number is, the more priority they have to be selected when facing conflict, thus resolving the conflict between UAVs and further achieving the full distribution of UAV swarms

5. Simulation Experiment

5.1. Validation Verification. Firstly, the effectiveness of the distributed cooperative strike decision-making method proposed in this work is verified. It is assumed that the UAV swarm consisting of 20 UAVs is sailing at the same speed and altitude and that the relevant information of 5 ground targets is obtained by reconnaissance at a certain time, as exhibited in Table 1. Meanwhile, the status parameters of the UAV swarm are presented in Table 2, and the position distributions of the UAV and the target are shown in Figure 8. The algorithm operation environment is the 12th Gen Intel(R) Core(TM) i7-12700H 2.70 GHz matlab2022a. The decision results are displayed in Table 3, and the corresponding allocation results are exhibited in Figure 9. In terms of the constraints, the angle between the UAV's flight line of sight and the target as indicated in Figure 9; the UAV characteristics, the target characteristics, and the decision results obtained all satisfy the relevant constraints.

5.2. Algorithm Comparison Experiment. The particle swarm optimization (PSO) algorithm always shows good performance in the optimization problem. Here, the distributed cooperative strike decision-making method is compared with the standard PSO algorithm and the improved particle swarm optimization algorithm (VPSO) presented in literature [23]. Besides, the decision results are calculated with Equation (18), to obtain the total income value. Also, judgment is given to the superiority of the distributed cooperative strike decision-making method.

The parameter settings of the improved particle swarm algorithm of the standard particle swarm algorithm are exhibited in Tables 4 and 5.

To facilitate the comparison, in this work, three scenarios with different UAV swarm sizes and different target numbers are set, the decision results of the three methods under 50 times of random distribution of UAVs and target positions are recorded, and the simulation results are obtained, as presented in Figures 10–12. As observed from Figures 10–12, the method proposed in this work has obvious advantages, by contrast with the traditional optimization algorithm for the distributed UAV colonies of different scales. Moreover, with this method, the decision results, causing the higher overall benefits of the distributed UAV colonies, can be obtained.

5.3. Discussion. The above experimental results provide the intuitive proofs of the effectiveness and superiority of the

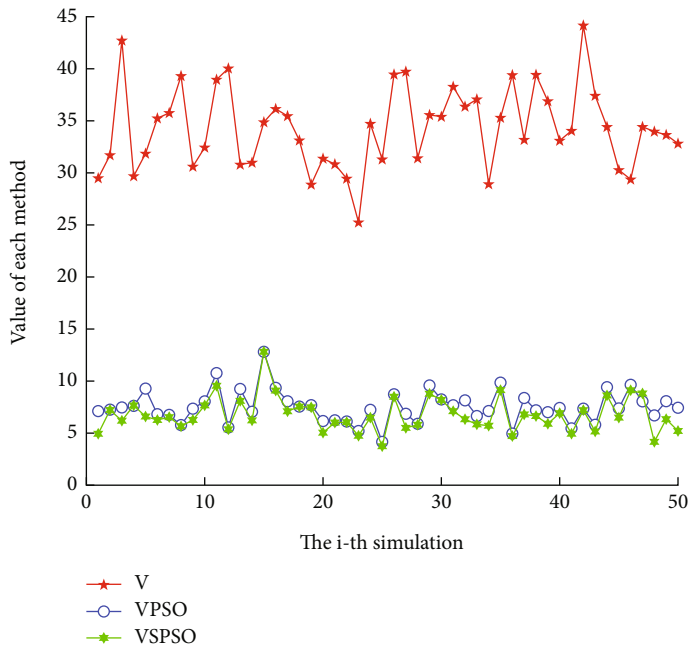


Figure 11: Value chart of decision results for that 30 UAVs which cooperate to strike 10 targets.

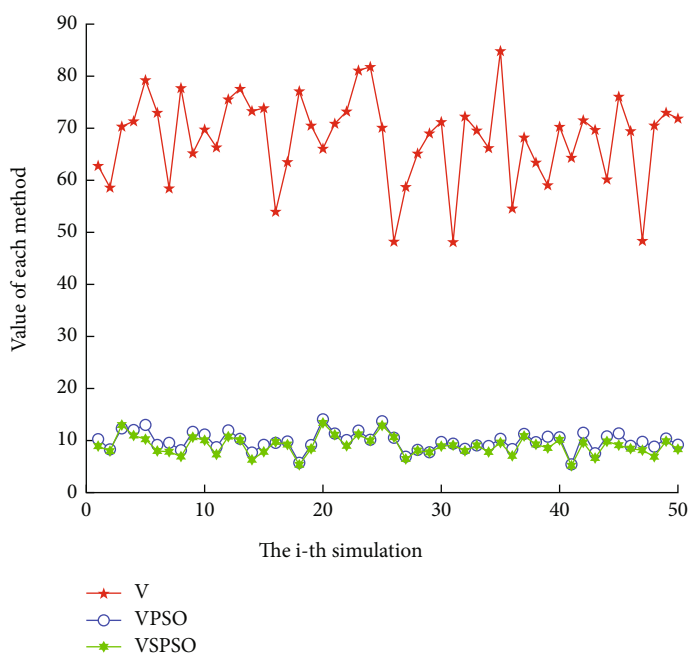


Figure 12: Value chart of decision results for that 50 UAVs which cooperate to strike 15 targets.

model established and the algorithm proposed in this work, with the explanations given from the following theoretical perspectives. Firstly, the model exhibited in Equation (18) embodies the multiple objectives such as the closest flight distance, the shortest flight time, the satisfaction with the kinematic characteristics of the UAV, and the maximum net income obtained by the UAV swarm in one objective function by setting multiple constraints and formulating rules, thus reasonably avoiding the influence of multiple objectives on the net income and further preventing the UAV swarm from falling into a *. Hence, the model can help the UAV swarm in making decisions faster and more efficient. Secondly, in view of the distributed UAV swarm, each UAV is independent and has the same computational capability. As observed from Figure 6, the decision process of a single UAV involves merely two cycles. In each cycle, the concept of "near optimal" is discarded, and the current "optimal result" is calculated directly. The result of the process is related to the set number of iterations. Namely, the higher the number of iterations, the better the result of the

search, accompanied by the longer computing time. In addition, during the process of seeking the best, the single drone tends to find the individual "optimal result." This may conflict with the final result of seeking the best. Once there is conflict, the decision again will greatly increase the decision time, and the decision result still can not guarantee the overall optimality, thus aggrandizing the computational complexity greatly. Therefore, the distributed competitive cooperation method, by comparing with the swarm intelligence algorithm, can better obtain the attack decision results of the distributed UAV swarm.

6. Conclusions

On the basis of fully considering the characteristics of UAV flight motion, it decomposes the problem of distributed UAV bee swarm cooperative search and strike decision-making, establishes the distributed UAV bee swarm cooperative strike decision-making model, clarifies the relevant constraints, proposes the arc tangent trajectory planning method, constructs the profit function of decision-making structure, uses the graph theory to build a distributed communication network, and puts forward a distributed cooperative strike decision-making method in this work. The validities of the model and methods are confirmed by conducting simulation experiments. Different from the conventional optimization methods, the distributed cooperative strike decision-making method proposed in this work is more suitable for the distributed topology structure, fully considers the discreteness of the benefit function, and effectively solves the conflict between the UAV individuals and the UAV bees. By analyzing the simulation results, it is known that the proposed method can better adapt to the distributed cooperative strike problem.

Data Availability

Data and codes can be offered by contacting the authors if needed.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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