

## Research Article

# Multi-UAV Cooperative Task Assignment Based on Orchard Picking Algorithm

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## ABSTRACT

The multi-unmanned aerial vehicle (UAV) must autonomously perform reconnaissance-attack-evaluation tasks under multiple constraints in the battlefield environment. This paper proposes a nearest neighbor method designed with the shortest neighboring distance as an indicator which quickly solves the optimal sequence of multiple tasks for cooperative execution. Each target to be destroyed requires a different quantity of ammunition; a cooperative task assignment model for heterogeneous UAVs is established accordingly. Based on the nearest neighbor method, and with reference to fruit-picking techniques currently in use, a novel “orchard picking algorithm (OPA)” is investigated as well. This algorithm proposed in this paper is a heuristic algorithm, which has a broad application prospect in complex task assignment. A cooperative attack task assignment is simulated to test the performance of the algorithm. In essence, it balances the assignment of tasks, works within a brief execution time, and exhibits high flexibility, strong robustness, and scalability.

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## 1. INTRODUCTION

The unmanned aerial vehicle (UAV) has the advantages of strong continuous combat capability, high maneuverability, and environmental adaptability due to the fact that they are not controlled by pilots [1–4]. In the process of actual combat, due to the complex and varied environment and wide distribution of targets, it usually requires multiple UAVs to cooperate with each other to carry out tasks [5], which makes the task execution time shorter and the completion rate higher [6,7]. Optimal decisions need to be taken for various mission-critical operations performed by UAVs [8]. The assignment of cooperative tasks to multi-UAVs refers to strategical execution of reconnaissance, attack, evaluation, and more for multiple targets within a certain area for multiple homogeneous or heterogeneous UAVs, thus maximizing the overall success of combat. The effectiveness of cooperative task assignment to multiple UAVs is an important indicator of the combat capability of UAVs.

Previous scholars have established various algorithms for the assignment of cooperative tasks to multi-UAVs. Author(s) [6–9], for example, proposed the fast task assignment (FTA) method algorithm based on Q-learning by neural network approximation and experience replay sequencing, which effectively transferred online computing to an offline learning process to assign tasks to heterogeneous UAVs under the condition of environmental uncertainty. A brain storm optimization was improved by local search procedure that each new candidate solution moves to the local best position

thus reducing computational time [10]. Jia *et al.* [11] took the two-stage stochastic programming model as a research object to transform the problem of optimizing combinations of heterogeneous UAVs into a problem of assigning cooperative multi-tasks with random speeds and time windows. They established a heuristic algorithm based on improved genetic algorithms accordingly [7,12,13]. A new prediction strategy was proposed based on center points and knee points under an adaptive diversity maintenance strategy [14]. A number of random individuals corresponding to the difficulty of the problem are generated to maintain proper population diversity and this is an effective evolutionary dynamic multi-target optimization method.

A new multi-objective genetic algorithm was proposed recently which is based on a mixed fitness function and Pareto-based measures [15]. The optimal solution is sought to resolve complex task programming with regard to UAVs and ground control systems [16,17]. The algorithms cannot be programmed online in real time, however, making it difficult to respond to sudden threats. In an effort to remedy this, Ziyang Zhen *et al.* [18] explored cooperative search-attack tasks with dynamic targets and threats and they proposed a distributed intelligent self-organizing task planning algorithm for multiple UAVs accordingly.

Many targeted heuristic algorithms have been applied to solve multi-target optimization problems in recent years [19–21], but there is currently no general cooperative task assignment model that can simultaneously meet complex battlefield environments with coupled task relationships and strict requirements for the task

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timing sequence. Although existing algorithms cannot guarantee optimal results, they do provide satisfactory solutions within an acceptable time period [22,23]. As the scale of the problem increases, the amount of algorithm calculation increases exponentially and thus the calculation time increases significantly [24]. However, most previous researchers have set cost functions according to the importance of the target and the capabilities of the UAVs in the process of multi-task assignment. Only the requirements of the task group for the number of UAVs is given, which does not account for the essential characteristics of the tasks.

When implementing cooperative reconnaissance, attack, and evaluation tasks, multiple unmanned aerial systems need to consider their own load constraints, mission sequence, and target position. Multi-UAV systems perform multiple tasks in the face of multiple targets, it will be better to find an algorithm with short computation time and balanced allocation. The purpose of the present study is to develop a practical algorithm to directly assign tasks for multiple targets with different needs. Inspired by the efficiency with which fruit farmers harvest their product, a novel multi-task assignment algorithm was established which regards the target group as “fruit trees,” the target characteristics as “fruits” of varying dimensions, and the UAVs performing tasks as “fruit farmers” picking the “fruit” according to the optimal strategy. The multi-task distribution is thus completed accurately at an acceptable cost.

The organizational structure of the paper is as follows. Section 2 establishes a multi-task model based on the nature of the multi-UAV tasks. Section 3 discusses the targets, realizations, and optimal evaluation indexes. Section 4 outlines the principle of the orchard picking algorithm. Section 5 gives the results of the simulation conducted to test the proposed method. Section 6 provides a brief summary and conclusion.

## 2. ESTABLISHMENT OF MODELS

The multi-target reconnaissance-attack-evaluation tasks were modeled first, then the corresponding parameters of UAVs and tasks were defined. Constraints were placed appropriately on the reconnaissance-attack-evaluation task planning mode [25], then mathematical expressions for the problem of task assignment in question were established as discussed in detail below.

### 2.1. Background Description

If the position of the enemy target group on the battlefield is known, it is necessary to perform reconnaissance-attack-evaluation tasks for the enemy target group. Each target needs at least one device for detailed reconnaissance and at least one type of ammunition for each target to be destroyed. Likewise, at least one image acquisition device is required for each target to be evaluated.

There is no coupling relationship between various tasks in this case, that is, each task can be executed in the order of reconnaissance, attack, and evaluation. If each UAV can carry only one reconnaissance device, one type of ammunition, or one image acquisition device, all the UAVs that perform tasks jointly form a heterogeneous UAV group. The modern battlefield has harsh environment and strict, brief timeline characteristics. To function properly in this environment, the UAVs must complete specified tasks in the shortest possible time.

### 2.2. Definition of Symbols

Reconnaissance, attack, and evaluation are the main UAV tasks during battle, and there are timing constraints between the three types of tasks. The two triples discussed here represent the amount of ammunition for the target to be completely destroyed and the UAV ammunition loading capacity, respectively. The triplet is the set of the target task demands and  $T = \{D_T, A_T, V_T\}$  indicates the UAV load task set, where the subscripts  $T$  and  $U$  indicate belonging to the task and belonging to the UAV, respectively.  $D$ ,  $A$ , and  $V$  indicate the reconnaissance task set, the attack task set, and the evaluation task set, respectively.

It should be noted that the target's demand for UAVs is not only quantitative but also relates to the load properties. It is not appropriate in this case to assign weight to the target value using the method presented above in the Introduction section. Whether the task can be fully executed depends on the geometric relationship of the two triples, that is, for  $\forall C, \exists T \subseteq U$ , where  $C$  is the set of target constraints and UAV constraints.

Consider the UAV cooperative attacks as an example. It is necessary to satisfy  $A_T \subseteq A_U$ . Let  $T = \{T_1, T_2, \dots, T_{N_t}\}$  denote  $N_t$  sets of targets. Any target requires different numbers and types of missile attacks. Let  $U = \{U_1, U_2, \dots, U_{N_u}\}$  represent a set of  $N_u$  UAVs which carry different types of ammunition and are considered to be heterogeneous. The symbol  $N_a$  denotes the number of types of missiles required by the target, the numbers of the same type of missiles are also different. The type and number of missiles required to destroy the  $j$ -th target are denoted by  $N_j^q$  ( $j = 1, 2, \dots, N_t; q = 1, 2, \dots, N_a$ ).

It is worth noting that the above symbol definition directly quantifies the target's property requirements rather than assigning weighted values, as is typically the case. The solution result so sought is more realistic. Similarly, this method is also applicable to task assignment in cooperative reconnaissance and cooperative evaluation contexts, which are not described in detail here.

### 2.3. Mathematical Modes

The assignment of cooperative tasks to multi-heterogeneous UAVs can be expressed as a combinatorial optimization problem [26]. The total number of  $q$  type missiles required for all targets to be destroyed is

$$N_q^a = \sum_{j=1}^{N_t} N_j^q, q = 1, 2, \dots, N_a \quad (1)$$

and the total amount of ammunition required to destroy all targets is

$$N_T^a = \sum_{q=1}^{N_a} N_q^a \quad (2)$$

Equations (1) and (2) represent the sum of the type of ammunition and the amount of ammunition required for all enemy targets to be completely destroyed. The resources carried by the task-performing UAVs must not be fewer than the required quantity.

There are a total of  $N_u$  heterogeneous UAVs. Each type of UAV can only carry one type of missile. There are a total of  $N_{ua}$  ( $N_{ua} \geq N_a$ ) types of UAVs in this case. Similarly, the number of  $p$  types of missile carried by the  $i$ -th UAV is  $N_i^p$ , ( $i = 1, 2, \dots, N_u; p = 1, 2, \dots, N_{ua}$ ). The constraint ( $p = 1, 2, \dots, N_{ua}$ ) must be satisfied, where  $N_i^{pf}$  is the amount of the  $p$ -type ammunition fully loaded by the  $i$ -th UAV. The total amount of  $p$ -type missiles carried by all UAVs is

$$N_p^a = \sum_{i=1}^{N_u} N_i^p, p = 1, 2, \dots, N_{ua} \quad (3)$$

The total amount of missiles carried by all UAVs performing tasks is

$$N_U^a = \sum_{i=1}^{N_u} N_p^a, U = 1, 2, \dots, N_u \quad (4)$$

If all targets can be destroyed, the amount of ammunition carried by the UAVs scheduled to perform the task is not less than the amount of ammunition required for the targets to be destroyed. Thus,

$$N_U^a \geq N_T^a \quad (5)$$

Formula (5) gives the constraint relationship between the total demand of the task and the total load capacity of the UAV. The purpose of this work is to cooperatively program local tasks under the overall constraint framework. Accordingly, for the multi-task and multi-constraint problem, a task assignment strategy directly specific to the task sequence was established.

### 3. ANALYSIS OF PROBLEMS

#### 3.1. Relationship Between Capabilities

Formula (5) can only guarantee the overall combat capability required by the UAV under the condition that all targets are completely destroyed. The task sequence and execution strategy cannot be obtained by this formula.

The battlefield environment is highly complex and destroying the target group in the shortest amount of time possible is the key to victory in combat. Thus, maximum efficiency (i.e., “the shortest time”) is taken the optimal evaluation index in this study. Without considering the time spent by the UAV to drop ammunition, the path from the initial position to the target position is the shortest possible and accordingly the time required to complete this task is also the shortest.

The UAV  $i$  carrying the  $p$ -type ammunition flies from the base to the targets  $S_T = \{j, j+1, j+2, \dots, j+s_i-1\}$  in its proper turn and returns to the base immediately after its ammunition is exhausted. The number of targets the UAV passes by  $s_i$ , so there is always a unique  $s_i$  that satisfies the following relationship:

$$\sum_j^{j+s_i-2} N_j^{q_k} \leq N_i^{p_k} \leq \sum_j^{j+s_i-1} N_j^{q_k}, k = 1, 2, \dots, N_{ua} \quad (6)$$

where  $q_k$  and  $p_k$  correspond to the same type of ammunition. Formula (6) ensures that the UAV that performs the task always returns

after dropping its last piece of ammunition. The order and number of targets required to be passed by all UAVs carrying  $p$ -type ammunition are

$$S^p = \{s_1, s_2, \dots, s_{N_u}\}, p = 1, 2, \dots, N_{ua} \quad (7)$$

where  $S_p$  is the number of tasks and the task sequence of all UAVs corresponding to all the targets, which is the set to be solved.

The amount of ammunition carried by each UAV cannot always meet the amount of ammunition required by the target in an integer. In other words, there is always one target that requires cooperative attacks by multiple UAVs or one UAV that can attack multiple targets in a real-world combat scenario.

#### 3.2. Optimal Evaluation Indexes

The set  $S_p$  determines the strategy used by a UAV to perform its tasks. Any UAV  $i$  carrying type  $p$  ammunition performs a given mission according to the target sequence  $s$ . The range from the base to the completion of the task is

$$L_i = |l_0 l_j| + \sum_j^{j+s-1} |l_j l_{j+1}|, i = 1, 2, \dots, N_u \quad (8)$$

where  $|l_0 l_j|$  indicates the range from the starting point to the first target and  $|l_j l_{j+1}|$  indicates the range determined by  $s_i$  from target  $j$  to target  $j+1$ . Accordingly, the optimal total range for all UAVs is

$$\text{Min: } L = \sum_{i=1}^{N_u} L_i \quad (9)$$

Equation (9) considers the urgency of the combat task to be completed within the shortest possible range. Therefore, the optimal programming of the task set  $S_p$  ( $p = 1, 2, \dots, N_{ua}$ ) should encompass the ability of all UAVs to reach all targets in the shortest time possible rather than the voyage of returning by the UAV after completing the task.

#### 3.3. Task Sequence

According to the model presented above, a nearest-neighbor method was established in this study based on the shortest adjacent target range and compared against another method which solves large-scale, multiple traveling salesman problems via ant colony-Partheno genetic algorithms. Under this method compared against the proposed method [14], the multi-target optimization problem is regarded as a large-scale multi-traveling salesman problem. The task sequence of the  $N_t$  targets solved is expressed as

$$T' = \{T'_1, T'_2, \dots, T'_{N_t}\} \quad (10)$$

The multi-traveling salesman problem centers on the shortest distance traveled by the salesman who travels from the starting target, passes by several required targets, and reaches its respective termination targets on the premise of the minimum and maximum requirements of the number of “cities” that each salesman

must visit. However, in an actual battlefield, time is one of the most important measures of task effectiveness; performing all tasks in the shortest time possible is the most effective strategy.

The nearest-neighbor strategy proposed in this paper comes always at the cost of an increase in the range of returning by the UAV after it completes the task. The closest next target is always selected, namely,

$$T^{q_k} = T_j^{q_k}, l(T_j^{q_k}) \leq l(T_{\bar{j}}^{q_k}) \quad (11)$$

where  $T^{q_k}$  represents the next target to be attacked by the UAV carrying the  $p_k$  type ammunition,  $l(T_j^{q_k})$  denotes the range from the current target position  $j$  of the UAV to the next target position, and  $\bar{j}$  indicates the set of other targets apart from target  $j$ . Each UAV ultimately selects the target closest to its current position in turn so that the UAV completes the process from taking off to dropping ammunition in the shortest possible amount of time.

The description of the target demand in the model has an additional dimension  $q_k$ , so the original binary variable becomes the ternary variable  $x_{ij}^p$  ( $p = 1, 2, \dots, N_{ua}$ ) and the optimal index function becomes

$$\min w = \sum_{i=1}^{N_u} d_{0s_i} + \sum_{i=1}^{N_u} \sum_{j=1}^{N_t} \sum_{p=1}^{N_{pf}} d_{ij}^p x_{ij}^p \quad (12)$$

where  $d_{0s_i}$  represents the range of the UAV from the base to the first target point,  $N_{pf}$  is the number of types of ammunition,  $d_{ij}^p$  indicates the range of the UAV carrying the  $p$ -type ammunition from target  $i$  to target  $j$ , and  $x_{ij}^p \in \{0, 1\}$  denotes whether the UAV carrying the  $p$ -type ammunition flew from the target  $i$  to target  $j$  or not.

## 4. THE ORCHARD PICKING ALGORITHM

Bionic algorithms have been used increasingly frequently in recent years to solve multi-target optimization problems [27] and generally provide satisfactory solutions. A novel algorithm for cooperative attacks on multiple targets by multiple UAVs was established in this study as inspired by fruit-picking methods.

Multiple fruit trees are distributed in an orchard of a certain area. Each fruit tree bears different numbers of fruits of different sizes. There are multiple fruit farmers carrying a pack basket that can hold a certain number of fruits. Each farmer can only pick fruits of one certain diameter and is required to complete the picking task in the shortest possible time. This is a problem of optimal assignment. The “picking time” is directly related to the speed at which the farmer walks, the size of his basket, the number of fruit trees, the yield of the fruit, the distance between the warehouse and the orchard, etc. The fruit-picking process was evoked in establishing the proposed algorithm to solve the problem of multi-target assignment in cooperative attacks by multiple UAVs.

### 4.1. Algorithm Modeling

Assume that the area of the orchard has a range within which  $N_f$  fruit trees are distributed. The position distribution of each tree is

known. According to the difference in fruit diameters, the fruits to be picked are divided into  $N_d$  species. There is a total of  $N_p$  fruit farmers engaged in picking. Due to the limitation of picking tools, each fruit farmer can only pick fruit of a single diameter—there is also an upper limit on the number of fruits that can be carried by each farmer. A farmer returns to the warehouse (base) only when his basket is full.

According to the actual situation, each fruit farmer has a different walking speed, and the walking speed of the  $i$ -th fruit farmer is  $v_i$  ( $i = 1, 2, \dots, N_p$ ), and the maximum number of fruits that the  $i$ -th fruit farmer can carry at a time is  $N_{fi}$  ( $i = 1, 2, \dots, N_p$ ). Finally, all these fruits were picked strategically and cooperatively.

### 4.2. Analysis of the Algorithm

Naturally, each fruit tree has a singular and constant location. The closer it is to the warehouse, the shorter the time it takes to pick; it is also picked faster by a farmer who walks at a greater speed. Efficiency is also greater if a farmer picks a larger number of fruits in a single picking iteration, and/or if a greater number of farmers are engaged in the picking process. Each farmer selects the tree closest to his current location or closest to the warehouse for picking depending on the current carrying capacity of his basket, the distribution of nearby trees, and the number of fruits on them. In other words, the picking task for each farmer is locally optimal.

According to the previous assumptions, the total task load of picking  $T_i$  for the  $i$ -th farmer is

$$T_i = \sum_j^{j+s_i-1} N_j^k + N_*^k, \left( k \in N_j^d, i = 1, 2, \dots, N_p \right) \quad (13)$$

where  $s_i$  denotes the number of trees to be picked from by the  $i$ -th farmer to fill his basket;  $N_j^k$  represents the number of fruits of the  $k$ th diameter on the  $j$ -th tree; and  $N_*^k$  indicates the number of fruits picked on the tree from which the fruits were picked last. In fact, each farmer actively selects the closest tree to pick from according to the predetermined number of trees. This allows the path given by  $s_i$  to be minimized.

As the information on the  $k$ -th diameter is already included in  $s_i$ , Formula (10) can be simplified and expressed in the orchard picking algorithm as follows:

$$L_{total} = \sum_{j=1}^{N_f} \sum_{i=1}^{N_p} (d_{0,i} + d_{j,s_i}) \quad (14)$$

where  $d_{0,i}$  represents the distance walked by the  $i$ -th farmer from the starting point to the beginning of the picking process on the first tree.  $d_{j,s_i}$  denotes the distance walked by the  $i$ -th farmer determined by the set  $s_i$  ( $s_i \in \{s_1, s_2, \dots, s_{N_p}\}$ ) from the first tree at which the picking began to the last tree at which point his basket was filled.

Each farmer uses the optimal available plan to complete the picking process, i.e., whichever approach allows him to fill his basket the quickest. This is exactly the result desired to solve the problems raised in the multi-UAV problem at the center of the present study.



## 5. SIMULATION AND VERIFICATION

### 5.1. Description of Problems

The proposed orchard picking algorithm was numerically simulated to test its performance. It was assumed in this case that the distribution of the target positions was as shown in Table 1. The types of ammunition (three in total) and quantity distribution required for target destruction were as shown in Table 2. If both the quantity of UAVs and ammunition at the base are sufficient, multiple heterogeneous UAVs carry different types and quantities of ammunition to cooperatively attack a target group in a certain area. Considering the inherent urgency of the battlefield and the need to take into account combat costs, once a task begins, the UAV does not return to the base to replenish its ammunition.

There are also three types of UAVs corresponding to the three types of ammunition. It is assumed that the UAV carrying A1 ammunition can carry 6 A1s, the UAV carrying A2 ammunition can carry 4 A2s, and the UAV carrying A3 ammunition can carry 4 A3s. The three types of UAVs have the same flight speed, 180 km/h, and a maximum flight time of 6 hours. The base coordinate position is (10 km, 10 km) and the number of UAVs is sufficient. According to the calculation process outlined above, at least 4 UAVs carrying A1 ammunition, 4 UAVs carrying A2 ammunition, and 4 UAVs carrying A3 ammunition should be flown.

### 5.2. Solving Task Sequence

The above problem was also converted into a multi-traveling salesman problem [14] to form a reference sequence for the shortest range: base  $\rightarrow$  T4  $\rightarrow$  T8  $\rightarrow$  T9  $\rightarrow$  T7  $\rightarrow$  T2  $\rightarrow$  T3  $\rightarrow$  T5  $\rightarrow$  T6  $\rightarrow$  T1. The task profile determined according to the traveling salesman algorithm as shown in Figure 1.

According to the nearest-neighbor method proposed here, when the UAV performs multiple tasks, it always selects the target closest to the current position. The reference sequence is thus base  $\rightarrow$  T4  $\rightarrow$  T8  $\rightarrow$  T9  $\rightarrow$  T7  $\rightarrow$  T5  $\rightarrow$  T3  $\rightarrow$  T2  $\rightarrow$  T6  $\rightarrow$  T1. A solution is derived according to the proposed algorithm on the task profile shown in Figure 2.

As shown in Figures 1 and 2, the traveling salesman [14] and nearest-neighbor method can both solve the task sequence. The former is based on overall optimization and the latter is mainly based on local optimization. In each method, the seventh UAV has the

largest task load and is responsible for the targets T2, T3, T6, and T1. Accordingly, compared with other UAVs, it has a longer range and takes the longest time to complete its task. The locally optimal task assignment scheme of either reference sequence can be obtained by the orchard picking algorithm.

### 5.3. Analysis of Results

The nearest-neighbor method proposed in this paper is nearly identical to the task reference sequence obtained by the traveling salesman method. The difference is that the former involves making minor adjustments to part of the task sequence and requires manual intervention to ensure a strategic task assignment. In order to prove the superiority of the orchard picking algorithm, this paper also takes particle swarm optimization algorithm and tabu search algorithm as the control group to solve the above problems respectively. The four methods were compared according to important indexes as shown in Table 3.

As shown in Table 3, when the same number of UAVs is deployed and the same amount of ammunition is given, both the nearest-neighbor method proposed in this paper and the method proposed in [18,23] can complete the task assignment. The total range of each method is about 2000 km and the total flight time is about 11 h. On the whole, both methods consume approximately the same amount of energy as well. The proposed method did not dramatically outperform the other method in this case. Particle swarm optimization algorithm and tabu search algorithm perform well in single task assignment, e.g., only attack task is performed without considering return time. However, in the implementation of the multi-task and multi-constraint problem of reconnaissance, attack, evaluation, and return trip with time constraints, these two algorithms are not as good as the orchard picking algorithm proposed in this paper.

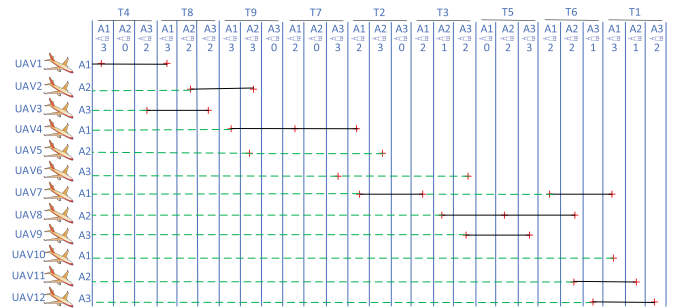


Figure 1 | Task profile based on multiple traveling salesman problem.

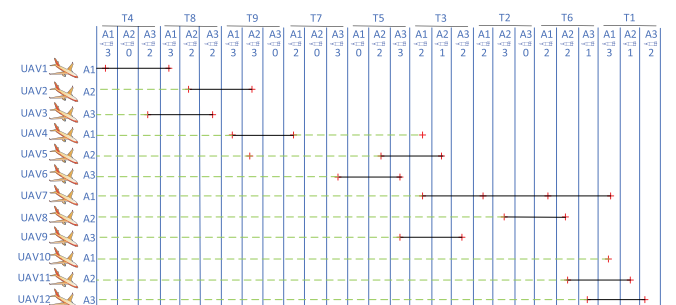


Figure 2 | Task profile based on nearest-neighbor method.

Table 1 | Distribution of coordinate positions of target group (unit: km).

Target	T1	T2	T3	T4	T5	T6	T7	T8	T9
X	26	83	71	37	59	29	84	55	61
Y	38	85	88	24	72	85	49	26	38

Table 2 | Types and quantities of ammunition required for target group to be attacked (unit: type and quantity).

Target	T1	T2	T3	T4	T5	T6	T7	T8	T9
A1	3	2	2	3	0	2	2	3	3
A2	1	3	1	0	2	2	0	2	3
A3	2	0	2	2	3	1	3	2	0

**Table 3** | Comparison of task performance between two methods.

Evaluation Index	Task Rate %	Task Time s <sup>-1</sup>	Total Range km <sup>-1</sup>	Return Range km <sup>-1</sup>	Total Range km <sup>-1</sup>	Total Voyage Time h <sup>-1</sup>
MTSP method	100	1.146	1256.213	753.075	2009.288	11.163
PSO method	100	1.324	1281.867	780.849	2062.716	11.460
TS method	100	1.285	1246.451	803.216	2049.667	11.387
Method proposed	100	0.810	1075.293	925.078	2000.371	11.113

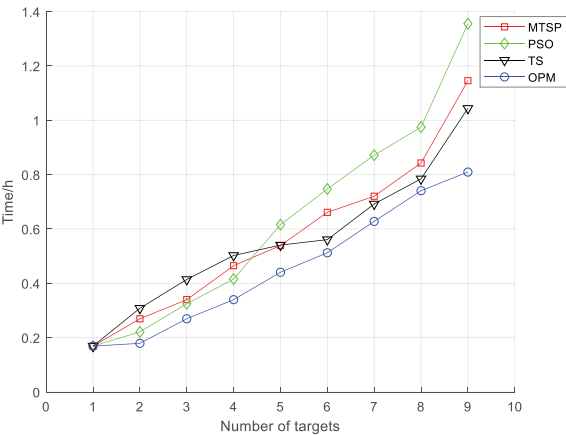
It is worth noting, however, that in terms of task completion time, the nearest-neighbor method is significantly better than the traveling salesman method [14,22]. The task completion time of the former is 1.146 h while that of the latter is only 0.810 h, marking time savings of 29%. In an actual combat scenario, the proposed method would result in the destruction of all enemy targets in a shorter time than the traveling salesman method. In order to verify the superiority of the algorithm proposed in this paper, the data used in the simulation experiment are simplified according to the actual battlefield target distribution. The orchard picking algorithm proposed in this paper not only considers the attributes of the task, but also considers the location distribution of the target group, which is an important index considered by the algorithm.

The primary evaluation criterion for task completion in this case is the time necessary to complete the last task, which depends on the UAV that performs the most tasks and has the largest range. An analysis of the relationship between target completion quantity and time is shown in Figure 3.

The results of the traveling salesman method and the proposed nearest-neighbor, orchard picking method are both satisfactory, as shown in Figure 3. The time spent to complete the task gradually increases with the number of targets to be attacked. The task assignment of the latter is relatively uniform and the number of targets is approximately linearly related to the execution time. This is because the nearest-neighbor method can alter its task assignment strategy during execution. Due to the constraints of task sequence and return time, the optimization space of particles is no longer continuous, resulting in the longest convergence time of the particle swarm optimization algorithm. Tabu search algorithm can select the corresponding tabu search region according to the task constraints, which converges faster than particle swarm optimization algorithm, but it is easy to cause premature convergence, and it is difficult to find the optimal solution. The orchard picking algorithm proposed in this paper can quickly search for the optimal solution in discontinuous space without local oscillation, and the convergence rate of the algorithm has an approximate linear relationship with the task size. As shown in Table 3, as there are slight differences between the total ranges. Increasing the return range cost reduces the task execution time, thereby ensuring that the UAV can complete the cooperative attack of multiple targets in the shortest possible time.

6. CONCLUSIONS

This study was conducted to establish a novel method for assigning tasks to heterogeneous UAVs in a time-critical combat environment. Multiple targets and multiple tasks were denoted as fruits on multiple fruit trees to be picked in an effort to mimic the strategy



**Figure 3** | Comparison of the four approaches.

used by farmers to harvest product. The orchard picking algorithm was established accordingly to solve the multi-target optimization problem. The algorithm works well under the given task requirements, avoids setting a complex cost function based on the tasks, and has high calculation efficiency.

A nearest-neighbor method was also established for the multi-task sequence with the shortest current distance as an index. Compared with the global optimal multi-traveling salesman problem, this method maintains the local optimum at all times. The orchard picking algorithm proposed in this paper can deal with the time series constraints of different tasks well, and the convergence time is faster than that of particle swarm optimization algorithm, and it does not fall into local optimum as easily as tabu search algorithm. It also works at a significantly lower task execution time on the premise that the total consumption remains almost unchanged. In future research, an adaptive strategy of task cooperative assignment will be introduced on the basis of the orchard picking algorithm proposed in this paper, so that the task load of each UAV is relatively balanced to adapt to the battlefield situation in real time.

CONFLICTS OF INTEREST

The authors declare they have no conflicts of interest.

AUTHORS' CONTRIBUTIONS

Weiheng Liu, Xin Zheng and Harish Garg conceived and worked together to achieve this work. Weiheng Liu was responsible for

investigation, conceptualization, methodology, analysis and writing original draft. Xin Zheng was responsible for conceptualization, validation, supervision, and funding acquisition. Harish Garg was responsible for conceptualization and analysis. All the authors wrote, edited and revised the article.

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## REFERENCES

- [1] E. Sepulved, H. Smith, Technology challenges of stealth unmanned combat aerial vehicles, *Aeronaut. J.* 121 (2017), 1261–1295.
- [2] J. Liu, W. Wang, X. Li, Solving a multi-objective mission planning problem for UAV swarms with an improved NSGA-III algorithm, *Int. J. Comput. Intell. Syst.* 11 (2018), 1067–1081.
- [3] J.K. Shiao, D. Ma, C.W. Chiu, J. Shi, Optimal sizing and cruise speed determination for a solar-powered airplane, *J. Aircraft.* 47 (2010), 622–629.
- [4] L.W. Traub, Range and endurance estimates for battery-powered aircraft, *J. Aircraft.* 48 (2011), 703–707.
- [5] R.M. Cummings, A. Schuette, Integrated computational experimental approach to unmanned combat air vehicle stability and control estimation, *J. Aircraft.* 49 (2012), 1542–1557.
- [6] A. Akbarimajd, G. Simzan, Application of artificial capital market in task allocation in multi-robot foraging, *Int. J. Comput. Intell. Syst.* 7 (2014), 401–417.
- [7] Y. Eun, H. Bang, Cooperative task assignment/path planning of multiple unmanned aerial vehicles using genetic algorithms, *J. Aircraft.* 46 (2009), 338–343.
- [8] S. Aggarwal, N. Kumar, Path planning techniques for unmanned aerial vehicles: a review, solutions, and challenges, *Comput. Commun.* 149 (2020), 270–299.
- [9] X. Zhao, Q. Zong, B. Tian, B. Zhang, M. You, Fast task allocation for heterogeneous unmanned aerial vehicles through reinforcement learning, *Aerosp. Sci. Technol.* 92 (2019), 588–594.
- [10] E. Tuba, I. Strumberger, D. Zivkovic, N. Bacanin, M. Tuba, Mobile robot path planning by improved brain storm optimization algorithm, in *IEEE Congress on Evolutionary Computation (CEC)*, Rio de Janeiro, Brazil, 2018, pp. 1–8.
- [11] Z. Jia, J. Yu, X. Ai, X. Xu, D. Yang, Cooperative multiple task assignment problem with stochastic velocities and time windows for heterogeneous unmanned aerial vehicles using a genetic algorithm, *Aerosp. Sci. Technol.* 76 (2018), 112–125.
- [12] J. Zou, Q. Li, S. Yang, H. Bai, J. Zheng, A prediction strategy based on center points and knee points for evolutionary dynamic multi-objective optimization, *Appl. Soft Comput.* 61 (2017), 806–818.
- [13] S. Obayashi, Y. Yamaguchi, T. Nakamura, Multi-objective genetic algorithm for multidisciplinary design of transonic wing planform, *J. Aircraft.* 34 (1997), 690–693.
- [14] C. Jiang, Z. Wan, Z. Peng, A new efficient hybrid algorithm for large scale multiple traveling salesman problems, *Expert Syst. Appl.* 139 (2020), 1128–1167.
- [15] E. Benini, R. Ponza, A. Massaro, High-lift multi-element airfoil shape and setting optimization using multi-objective evolutionary algorithms, *J. Aircraft.* 48 (2011), 683–696.
- [16] C.R. Atencia, G.B. Orgaz, M.D. Moreno, D. Camacho, Solving complex multi-UAV mission planning problems using multi-objective genetic algorithms, *Soft Comput.* 21 (2017), 4883–4900.
- [17] W. Liu, X. Zheng, M. Luis, H. Garg, Three-dimensional multi-mission planning of UAV using improved ant colony optimization algorithm based on the finite-time constraints, *Int. J. Comput. Intell. Syst.* 14 (2020), 79–87.
- [18] Z. Zhen, P. Zhu, Y. Xue, Y. Ji, Distributed intelligent self-organized mission planning of multi-UAV for dynamic targets cooperative search-attack, *Chinese J. Aeronaut.* 32 (2019), 2706–2716.
- [19] P. Lanillos, S.K. Gan, E.B. Portas, G. Pajares, S. Sukkarieh, Multi-UAV target search using decentralized gradient-based negotiation with expected observation, *Inf. Sci.* 282 (2014), 92–110.
- [20] P. Liu, Z. Ali, T. Mahmood, A method to multi-attribute group decision-making problem with complex q-rung orthopair linguistic information based on heronian mean operators, *Int. J. Comput. Intell. Syst.* 12 (2019), 1465–1496.
- [21] X. Zhang, S. Xia, X. Li, Quantum behavior-based enhanced fruit fly optimization algorithm with application to UAV path planning, *Int. J. Comput. Intell. Syst.* 13 (2020), 1315–1331.
- [22] Z. Zhen, D. Xing, C. Gao, Cooperative search-attack mission planning for multi-UAV based on intelligent self-organized algorithm, *Aerosp. Sci. Technol.* 76 (2018), 402–411.
- [23] G. Oh, Y. Kim, J. Ahn, H.L. Choi, Market-based distributed task assignment of multiple unmanned aerial vehicles for cooperative timing mission, *J. Aircraft.* 54 (2017), 2298–2310.
- [24] S. Rathinam, R. Sengupta, S. Darbha, A resource allocation algorithm for multivehicle systems with non-holonomic constraints, *IEEE Trans. Automat. Sci. Eng.* 4 (2007), 98–104.
- [25] J.H. Jafarian, E.A. Shaer, Q. Duan, An effective address mutation approach for disrupting reconnaissance attacks, *IEEE Trans. Inf. Forensics Secur.* 10 (2015), 2562–2577.
- [26] D.G. Bounds, New optimization methods from physics and biology, *Nature.* 329 (1987), 215–219.
- [27] P.A. Downing, A.S. Griffin, C.K. Cornwallis, Group formation and the evolutionary pathway to complex sociality in birds, *Nat. Ecol. Evol.* 4 (2020), 479–493.