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# Survey on Collaborative Task Assignment for Heterogeneous UAVs Based on Artificial Intelligence Methods

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## ABSTRACT

Heterogeneous unmanned aerial vehicle (UAV) swarms have garnered significant attention from researchers worldwide due to their remarkable flexibility, diverse mission capabilities, and wide-ranging potential applications. Mission planning stands at the core of UAV swarm operations, requiring consideration of various factors including mission environment, requirements, and inherent characteristics. In this paper, we investigate the model of the cooperative tasking problem in heterogeneous UAV swarms. We provide a comprehensive review of artificial intelligence algorithms applied in UAV swarm mission planning, analyzing their strengths and weaknesses in multi-UAV cooperative environments. By discussing these key techniques and their practical applications, the article highlights future research trends and challenges. This review serves as a valuable reference for understanding the current state of AI algorithm applications in heterogeneous UAV swarm task assignments.

## KEYWORDS

heterogeneous unmanned aerial vehicles (UAVs); collaborative task assignment; artificial intelligence methods

Unmanned aerial vehicles (UAVs) are characterized by high survivability, low cost, and flexibility[1], and are important combat equipment in modern warfare. After decades of research, UAV-related technologies have made remarkable progress and become more and more versatile, especially in surveillance[2, 3], photogrammetry[4], agriculture[5, 6], military[7], and civil security[8], which have a wide range of applications. From a military perspective, for example, UAVs have now become an increasingly important military tool. On the battlefield, unmanned aerial vehicles can gather intelligence, reconnoitre the enemy and carry out strike missions without being attacked by the enemy, among other things[9]. From the perspective of the civilian industry, UAVs can be used to monitor the condition of farmland, apply fertilizers and spray pesticides accurately, thereby improving the yield and quality of agricultural products. In the construction and real estate industries, UAVs are used for site monitoring and land mapping, helping to plan and design construction projects and improve engineering efficiency. UAVs also play a key role in environmental monitoring, monitoring air and water quality, tracking wildlife protection and being used for early environmental warnings. In addition, UAVs technology is playing an active role in areas such as power and infrastructure maintenance and medical rescue. Analysis shows that the growing trend of UAV applications in these areas will continue, and the need to increase efficiency, reduce costs, minimize risk and provide accurate data will continue to drive UAV technology.

However, the mission execution capability of a single UAV shows certain limitations, in the face of today's increasingly complex combat environment and multi-mission requirements[10]. Firstly, due to the limitation of on-board sensors and communication equipment, a single UAV has limited ability to perceive the mission environment; secondly, due to the limitation of its own fuel, the UAV has limited flight time and does not have the capability of high-intensity sustained combat; thirdly, once a single UAV is affected by a failure, the efficiency of mission execution will be drastically reduced, which may even lead to the termination of the mission in serious cases[11]. Therefore, the current application of UAVs is gradually developing towards clustering, and multiple-UAVs working together as a team will become a new mode of combat[12, 13]. Recently, developments in multi-intelligence cooperative control have facilitated mission synergy for UAV swarms in hazardous and uncertain environments[14–20].

UAV clusters include homogeneous UAV clusters and heterogeneous UAV clusters. Homogeneous UAVs refer to UAVs with the same combat capability and combat mode, on the contrary, heterogeneous UAVs refer to multiple types of UAVs with different combat capabilities, which can include reconnaissance aircraft, fighters, and so on[21, 22]. The application of homogeneous multi-UAVs in the Internet of Things (IoT) promotes efficient airborne data transmission. This technology is particularly suitable for operational scenarios with a single mission objective, simple combat scenarios and low mission complexity[23]. However, with the complexity of combat scenarios and the diversification of mission types, homogeneous UAV clusters with a single function are unable to complete complex missions alone, and the level of intelligence and heterogeneity of the multi-UAV cooperative combat system is gradually increasing, and heterogeneity will be the main direction of the future development of UAV[10].

The heterogeneous multi-UAV task allocation problem is a class of complex combinatorial optimization problems, which belongs to the category of task assignment and resource allocation. The problem mainly refers to assigning one or more ordered tasks to each UAV based on certain environmental information and

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task sets, so that the overall performance of the entire UAV formation is optimized while the tasks are completed, given that the types or numbers of UAVs are known[24, 25]. This problem can be divided into two subproblems: task allocation and trajectory planning[26, 27]. Obviously, the optimization of task allocation has an important impact for the operational efficiency of UAVs. Therefore, solving the task allocation problem of heterogeneous UAVs has become a prominent and important issue in the field of multi-UAV control[28].

The rest of the paper is structured as follows. Section 1 provides a brief overview of two classes of models used to solve the heterogeneous UAVs cooperative multi-tasking problem. In Section 2, the basic framework of group intelligence algorithms is summarized and the current research status of a variety of typical algorithms is presented, In Section 3, future research challenges and development directions for the multi-UAV collaboration problem are discussed. Section 4 concludes the paper.

## 1 Collaborative Task Assignment Model of Heterogeneous UAV

The heterogeneous properties of UAVs include differences in the weapons they carry, their functions, and operational characteristics. The heterogeneous UAV cooperative tasking problem refers to a combinatorial optimization problem that gives multiple UAVs with different performance to find a feasible solution to perform multiple tasks on multiple targets[29]. This issue requires not only the development of realistic distribution plans, but also ensuring the rapid and stable implementation of the distribution. As shown in Fig. 1, a simple scenario graph of multiple heterogeneous UAVs for mission planning with three UAVs of different performances, each UAV performs different missions (detection mission, attack mission, confirmation mission, etc.) on the target satisfying the relevant constraints. Two types of classical models for the UAV cooperative multiple task assignment problem are given below. In the first problem model, we examine UAVs equipped with different quantities of weapons, incorporating a finite limit on the number of weapons as a constraint in the problem. In the second model, we also consider UAVs with different characteristics (reconnaissance, attack, etc.), each of which is assigned a specific task based on its capabilities and the task adheres to prioritization requirements.

### 1.1 Modeling of UAV tasking problem based on carrying different number of weapons

There is flexibility in the choice of performance metrics for addressing the UAV cooperative tasking problem. In the following, we discuss two specific metrics: the first one is to minimize the time required for the entire UAV swarm to complete all the tasks, i.e., to minimize the longest working time among all the UAVs; and the second one is to minimize the total flying distance of the UAVs while performing all the tasks. It is assumed that all UAVs have constant and uniform speeds.

Shima and Schumacher[30, 31] selected the first criterion, the scenario examined involves two different types of UAVs: ground-attack UAVs equipped with large-area ground moving target indication (GMTI) Doppler radars, and a category consisting of multiple smaller UAVs with ground-attack capability, equipped with smaller-area GMTI Doppler radars. They operate together to detect and engage moving targets on the ground. Targets are designated by human supervisors or external agents. The long-range UAVs orbit outside the area of interest and maintain a fixed visual contact with the targets. It can continuously track targets that meet certain speed criteria. This alternative UAV can also track and attack targets. In order to reduce the uncertainty of target locations, two UAVs are responsible for tracking each target at appropriate angular intervals. While conducting the assault, the targets in the area are tracked by an alternate UAV cooperating with the standoff UAV or by another alternate UAV. The challenge is to automate tasking and path planning to meet tight time constraints for effective target tracking and engagement. Shima and Schumacher[30,31] set

$$U = \{0, 1, \ldots, Q_u\},$$

represents the group of collaborating UAVs, where 0 indicates an unarmed stand-off UAV and $Q_u$ denotes an alternate UAV carrying $Q_u$ GPS-guided munitions. Fuel constraints are not considered in the task allocation process. The set of targets for UAVs attack is

$$T = \{1, 2, \ldots, Q_t\}.$$

The set of stage in which three UAVs are assigned to each target is

$$S = \{1, 2, \ldots, Q_s\}.$$

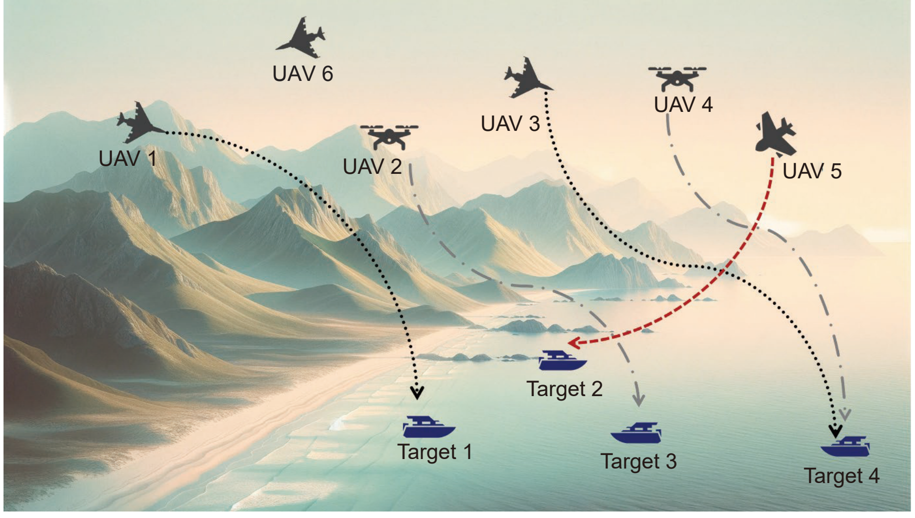


**Fig. 1 Heterogeneous UAV swarm tasking scenario.**

This collection of targets should be attended to by $Q_u+1$ collaborating UAVs. As each target needs to be serviced by three cooperating UAVs at a time, thus $Q_s=Q_t$. Let $x_{i,j,k}^{l,m}\in\{0,1\}$ be the decision variable which is equal to 1 if the UAVs $i,j,k\in U$, $i\neq j\neq k$ perform the prescribed task on target $m\in T$ in phase $l$, otherwise it equals 0. Let $t_{i,j,k}^{l,m}$ represent the amount of time taken by the group of three UAVs to complete the task assigned to target $m$ during phase $l\in S$, where $l$ belongs to the set $S$. Based on these, he problem model is given:

$$\min\ J_1=\max\sum_{m=1}^{Q_t}\sum_{i=0}^{Q_u}\sum_{j=0}^{Q_u}\sum_{k=1}^{Q_u}t_{i,j,k}^{l,m}x_{i,j,k}^{l,m} \tag{1}$$

Such that:

$$\sum_{m=1}^{Q_t}\sum_{i=0}^{Q_u}\sum_{j=0}^{Q_u}\sum_{k=1}^{Q_u}x_{i,j,k}^{l,m}=1,\ l\in S \tag{2}$$

$$\sum_{l=1}^{Q_s}\sum_{i=0}^{Q_u}\sum_{j=0}^{Q_u}\sum_{k=1}^{Q_u}x_{i,j,k}^{l,m}=1,\ m\in T \tag{3}$$

$$\sum_{i=0}^{Q_u}\sum_{j=0}^{Q_u}x_{i,i,j}^{l,m}+\sum_{i=0}^{Q_u}\sum_{j=0}^{Q_u}x_{i,j,i}^{l,m}+\sum_{i=0}^{Q_u}\sum_{j=0}^{Q_u}x_{i,j,j}^{l,m}=0,\ l\in S,\ m\in T \tag{4}$$

$$x_{i,j,k}^{l,m}\in\{0,1\},\ \ l\in S,\ m\in T,\ i,j,k\in U \tag{5}$$

The constraint Eq. (2) indicates that at each stage there is only one goal $m\in T$ served by the UAV group, Eq. (3) denotes that each goal $m$ is served only once in all stage, Eq. (4) guarantees that a single UAV will not be allocated to carry out multiple assignments for a single target, i.e., each target is serviced by three different UAVs.

Shima and Schumacher[31] explored a heterogeneous trio of UAVs, each UAV is equipped with specialized sensors and all but one is armed. In order to effectively attack the target, two UAVs must simultaneously track the target while the third UAV carries a weapon to carry out the attack. Assuming that each UAV $k\in U\setminus\{0\}$ carries a limited number of strike weapon (denoted by $w_k$), this restriction limits the number of times each UAV can strike a target. The corresponding constraint is

$$\sum_{l=1}^{Q_s}\sum_{m=1}^{Q_t}\sum_{i=0}^{Q_u}\sum_{j=0}^{Q_u}x_{i,j,k}^{l,m}=w_k.$$

The second performance criterion: sum of distances for all tasks performed by UAVs was considered by Shima et al.[32] In the scenario studied in Ref. [32], there are three types of tasks to be performed by UAV swarms: classify, attack, verify and $Q_m$ is a quantity of such tasks. Task allocation must consider several factors, including task prioritization, coordination, time constraints, and feasible flight paths. It is important to note that tasks related to each target must be executed in a sequential manner. This means that a target can only be subjected to an attack after it has been categorized, and verification of the target can only occur after an attack has been carried out on it. In addition, each task only needs to be executed once, that is, task coordination and UAVs are required to follow a flyable trajectory to perform a specific task within a given time frame.

The objective is to minimize the cost function $J_2$, which is given by Eq. (6). The variable $y_{l,i,j}$ is a binary decision variable that takes a value of 1 when, at stage $l$, UAV $i\in U$ is assigned to perform the specified tasks on target $j\in T$, and it takes a value of 0 otherwise. Let $Y_l=\{y_{1,i,j},y_{2,i,j},\ldots,y_{l,i,j}\}$ denote the distribution of tasks at stage $l$ and $c_{l,i,j}^{Y_{l-1}}$ denote the distance between UAV $i$ and target $j$, taking into account the assignment history that precedes stage $l$ as denoted by $Y_{l-1}$; $r_{l,i,j}^{Y_{l-1}}$ represents the resource, such as fuel, needed to execute the mission, while $b_i$ denotes the available resources for UAV $i$ within the set $U$.

$$\min\ J_2=\sum_{l=1}^{Q_s}\sum_{i=1}^{Q_u}\sum_{j=1}^{Q_t}c_{l,i,j}^{Y_{l-1}}y_{l,i,j} \tag{6}$$

Such that:

$$\sum_{i=1}^{Q_u}\sum_{j=1}^{Q_t}y_{l,i,j}=1,\ l\in S \tag{7}$$

$$\sum_{l=1}^{Q_s}\sum_{i=1}^{Q_u}y_{l,i,j}=Q_m,\ j\in T \tag{8}$$

$$\sum_{l=1}^{Q_s}\sum_{j=1}^{Q_t}r_{l,i,j}^{Y_{l-1}}y_{l,i,j}\leqslant b_i,\ i\in U \tag{9}$$

$$y_{l,i,j}\in\{0,1\},\ \ l\in S,\ i\in U,\ j\in T \tag{10}$$

The constraint Eq. (7) denotes that the target $j\in T$ has a task assigned to UAV $i\in U$ at each stage. Equation (8) denotes that $Q_m$ tasks need to be performed on target $j$. Formula (9) indicates that the total consumption of resources by each UAV $i\in U$ is not more than its capacity.

### 1.2 Modeling the UAV tasking problem based on different performances

The cooperative multiple assignment problem is a computationally intractable problem. In order to implement the optimisation process, the researchers approximated this problem as a graph based on the heading angle discretization[33–35].

Let

$$T_{\text{all}}=\{T_1,T_2,\ldots,T_{Q_T}\},$$

denote a set of $Q_T$ targets with known locations. Each of these targets is assigned various tasks that require execution. During this allocation process, the UAVs are tasked with visiting each target and accomplishing a set of $M_T$ tasks, where $M_T$ is a subset of

$$M=\{C,A,V\},$$

with $C$ representing classification, $A$ representing attack (which can further be categorized as single attack $A_s$ or double simultaneous attack $A_d$ depending on the target type), and $V$ representing verification. $A_d$ consists of two strike tasks performed by two different UAVs. In addition, the mission execution by UAVs must adhere to the prioritization requirement, meaning that a target can only be subjected to an attack after it has been classified, and it can only be verified after an attack has been executed on it.

Let $Q_{m_T}$ denote the number of tasks that the goal $T\in T_{\text{all}}$ is made to execute, so $Q_{m_T}=M_T$. It is worth noting that each task can only be executed once, except for tasks $A_d$, which can be executed twice. Hence, the total number of tasks to be executed by the UAVs in the entire scenario is denoted as

$$Q_{\text{all}} = \sum_{T \in T_{\text{all}}} Q_{m_T}.$$

Suppose $Q_C$, $Q_V$ represent the number of targets to be identified and verified, respectively, and $Q_{A_s}$, $Q_{A_d}$ represent the number of targets to be struck in a single strike and double strike, where the integers $Q_C, Q_V, Q_{A_s}, Q_{A_d} \in [0, Q_T]$ and $Q_{A_s} + Q_{A_d} \leqslant Q_T$, thus

$$Q_{\text{all}} = Q_C + Q_V + Q_{A_s} + 2Q_{A_d}.$$

The set of $Q_U$ collaborative heterogeneous fixed-wing UAVs is

$$U_{\text{all}} = \{U_1^t, U_2^t, \ldots, U_{Q_U}^t\},$$

where $t$ represents the category of UAVs. In this problem, we consider three different types of UAVs, as shown in Table 1.

Utilizing the set of heading angle discretizations denoted as

$$H = \{\psi_i : \psi_i = 2\pi i / Q_\psi,\ i = 0, 1, \ldots, Q_\psi - 1\},$$

where the positive integer $Q_\psi$ represents the desired resolution for heading angles, to define the graphs. The set of vertices in the graph is

$$V_T = \{(T_1, \psi_1), \ldots, (T_i, \psi_j), \ldots, (T_{Q_T}, \psi_{Q_\psi})\},$$

where each node is identified by the position and heading angle $\psi \in H$ of a target $T_i \in T_{\text{all}}$, such that $\|V_T\| = Q_T Q_\psi$. The set of vertices for the initial position and heading of the UAVs is

$$\{(U_1^t, \psi_{1_0}), (U_2^t, \psi_{2_0}), \ldots, (U_{Q_U}^t, \psi_{Q_{U_0}})\},$$

where $\|V_U\| = Q_U$. The set of all vertices in the graph is $V = V_T \cup V_U$, $\|V\| = Q_V = Q_U + Q_T Q_\psi$, and the set of edges in the graph is

$$E = \{(v_i, v_j) | v_i \in V, v_j \in V_T\},$$

where $\|E\| = Q_E = Q_T Q_\psi (Q_U + Q_T Q_\psi)$.

Edison and Shima[35] and Deng et al.[33] chose to minimize the cumulative distance flown by all UAVs and minimize the execution time required for the UAVs to complete the task as the objective functions, respectively. Since the UAVs fly at a constant speed, these two types of objective functions are equivalent. The set

$$P_u = \{(v_i, v_j) | X_{(v_i, v_j)}^{u,k} = 1, v_i \in V, v_j \in V_T, k \in \{1, 2, 3\}\},$$

is the connected path of UAV $u \in U_{\text{all}}$. In the following, we give an example of a model for the task allocation problem by minimising the task completion time.

$$\min\ J_3 = \sum_{u=1}^{Q_U} \sum_{i=1}^{Q_V} \sum_{j=1}^{Q_T Q_\psi} \sum_{k=1}^{3} X_{(v_i, v_j)}^{u,k} w_{(v_i, v_j)}^k \tag{11}$$

Such that:

$$\sum_{u=1}^{Q_U} \sum_{i=1}^{Q_V} \sum_{l=1}^{Q_\psi - 1} \sum_{k=1}^{3} X_{(v_i, (T, \psi_l))}^{u,k} = Q_{m_T},\ \forall\, T \in T_{\text{all}} \tag{12}$$

$$t_C \leqslant t_{A_s} \leqslant t_V \tag{13}$$

$$t_C \leqslant t_{A_{d_1}} = t_{A_{d_2}} \leqslant t_V \tag{14}$$

$$\sum_{i=1}^{Q_V} \sum_{j=1}^{Q_T Q_\psi} X_{(v_i, v_j)}^{u,2} \leqslant n_u^a,\ \forall u \in U_{\text{all}} \tag{15}$$

$$X_{(v_i, v_j)}^{u,k} \in \{0, 1\},\ \forall v_i \in V, v_j \in V_T, k \in \{1, 2, 3\} \tag{16}$$

where $X_{(v_i, v_j)}^{u,k} = 1$ denotes the edge $e = (v_i, v_j)$ is served by UAV $u \in U_{\text{all}}$ performing task $k$, with $k = 1$ for classification task, $k = 2$ for attack task, and $k = 3$ for verification task; otherwise $X_{(v_i, v_j)}^{u,k} = 0$. $w_{(v_i, v_j)}^k$ is the cost of performing task $k$ along the edge $e = (v_i, v_j)$ for UAV $u$.

The constraint Eq. (12) represents the number of tasks that must be performed for each target. $t_m$ $(m = C, A, V)$ is the cumulative time from the start time of the target to the time of the mission executed by the UAV. The constraints Formulas (13) and (14) are time constraints that guarantee the priority of the mission execution. The former applies to targets that require a single attack and the latter applies to targets that require two simultaneous attacks. The last constraint Formula (15) states that weapon resources are finite. $n_u^a$ denotes the weapon limit of the *u-th* UAV. For reconnaissance drones, $n_u^a = 0$ because they carry no weapons.

Jia et al.[34] emphasizes a cooperative multi-tasking problem with random speeds and flexible time windows. They develop a two-stage on-the-fly planning model with the objective of optimizing task allocation in the first stage to minimize expected costs in the second stage. The first-stage task allocation is structured in a manner consistent with the approach described above.

**Table 1 UAV capabilities and assigned tasks.**

| Type | Capability | Task |
|---|---|---|
| Combat | Surveillance and attack | $\{C, A, V\}$ |
| Surveillance | Surveillance | $\{C, V\}$ |
| Munition | Attack | $\{A\}$ |

## 2 Intelligent Optimization Algorithm for Task Allocation

The task assignment problem for UAVs is generally characterized as cooperative multi-tasking assignment problem (CMTAP), multiple traveling salesman problem (MTSP), and other optimization problems[32, 36]. There are two commonly used solution methods for these problems: traditional optimization algorithms and intelligent optimization algorithms. The conventional techniques such as mixed integer linear programming (MILP)[37, 38], branch and bound (BAB) algorithm[37], and tree search algorithm (TSA)[39, 40] can obtain the optimal solution. However, MILP and BAB involve many complex matrix operations, and the search range of TSA is large, when solving large-scale complex task allocation problems. As the problem size increases, the efficiency decreases, making it challenging to obtain the optimal solution to the task assignment problem within a reasonable time frame using traditional methods.

Intelligent optimization algorithms are developed by simulating or emulating natural phenomena, processes, and intelligent behaviors observed in biological communities. These algorithms do not depend on the initial conditions and do not require a lot of gradient information, which can avoid the high computational complexity of NP-hard problems and efficiently achieve better quality solutions. Therefore, more and more scholars investigate the application of intelligent optimization algorithms to task allocation problems. Figure 2 illustrates the intelligent optimization algorithm’s process for addressing the multi-tasking assignment problem. The process is mianly divided into five stages. The first stage involves problem definition and preparation, where the aim is to articulate the problem, gather data, choose suitable algorithms and coding methods. The second stage encompasses initialization, which includes tasks such as initializing both the tasks and UAV state, selecting the initial strategy, and defining the fitness function. These steps contribute to furnishing the algorithm with an initial solution. The third stage focuses on optimization iteration, where the algorithm iteratively refines the solution. The fourth stage involves termination condition judgment, where the algorithm continues iterating until the termination condition is met. Upon satisfaction of the termination condition, the process proceeds to the final stage: result output and interpretation. In this section, we summarize the typical intelligent optimization algorithms for heterogeneous UAV swarm collaboration.

### 2.1 Genetic algorithm

The genetic algorithm is an optimization technique that emulates the process of evolution, proposed by professor Holland of the University of Michigan in 1969 and developed through

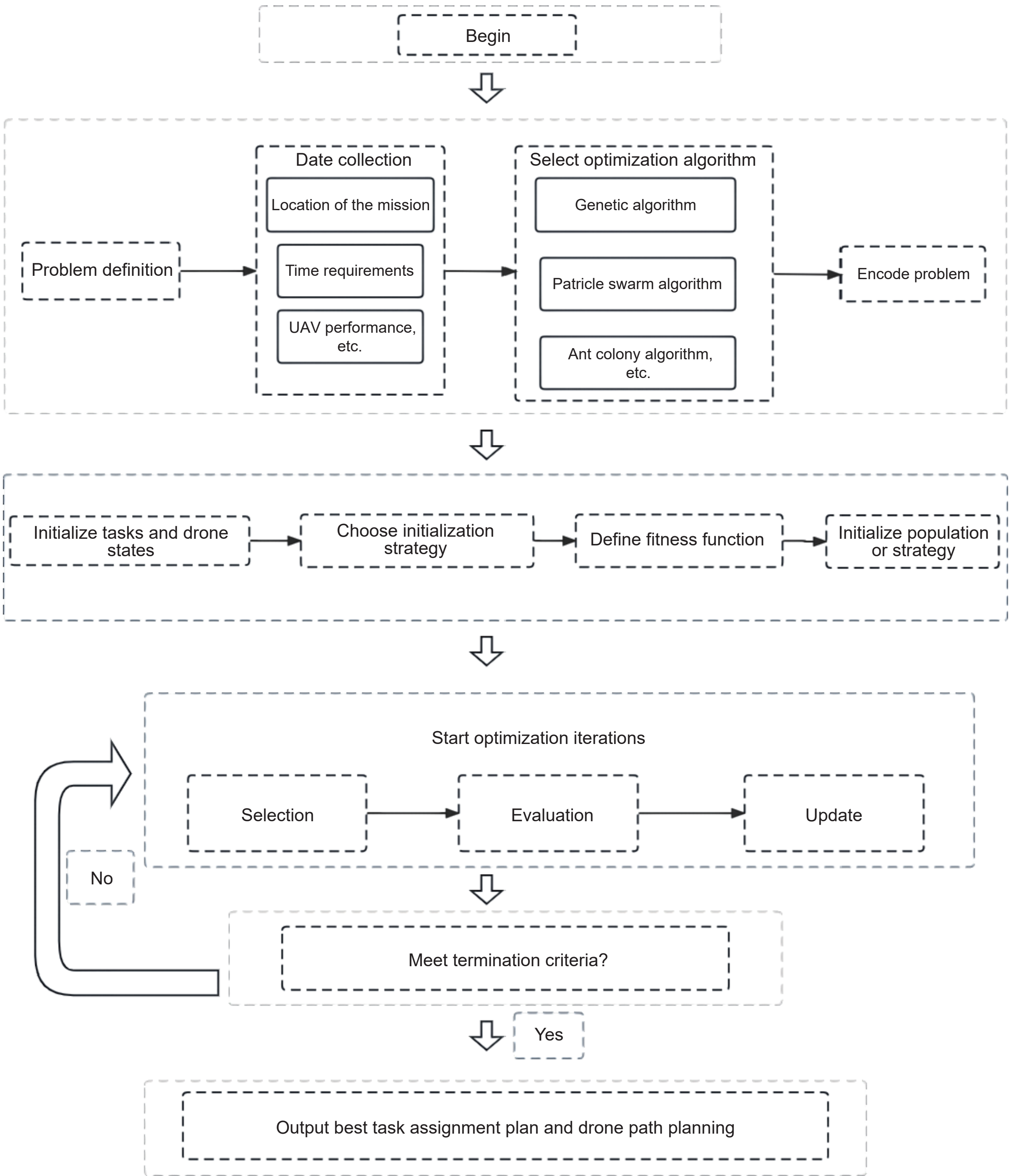


**Fig. 2 Basic framework of intelligent optimization algorithms for solving multi-tasking assignment problems.**

subsequent research[41, 42]. It is based on the principle of biological evolution and is used to solve extreme value optimization problems. Genetic algorithm simulates the biological genetic mechanism with self-organization and self-adaptation characteristics. It is widely used in the fields of control, science, engineering, etc. Especially, it is excellent in dealing with complex nonlinear and multidimensional optimization problems[43, 44]. However, it also suffers from the problems of insufficient local search ability and slow convergence speed, which need to be further improved. Genetic algorithms are uniquely suited for collaborative task assignment of heterogeneous UAVs. It can generate adaptable and diverse solutions through global search, adaptive evolution, and diversity maintenance. Meanwhile, it can solve constraint and nonlinear problems, adapt to different scenarios with interpretability, and improve the efficiency and performance of task allocation.

Considering the time constraints imposed by simultaneous missions and the interdependence between mission assignment and path planning for each UAV, in order to reduce the computational complexity, Shima and Schumacher[30] proposed a genetic algorithm that efficiently searches the feasible solution space and investigated the sensitivity to the performance of genetic algorithm tuning parameter variations. This algorithm can efficiently explore the space of feasible solutions and provide monotonically improved solutions. Its performance surpasses randomized search and can be applied to solve large-scale problems. Under the constraints of task priority and trajectory limitations, Shima et al.[32] established a genetic algorithm. Then they compared the performance of this algorithm with the randomized search method and the deterministic branch delimited search method through simulations under two different cost functions, showing the effectiveness of the algorithm. Good solutions can be found by exploring the space of feasible solutions. Therefore, the number of feasible solutions can serve as a measure of the computational complexity of the problem. The algorithm independently performs trajectory optimization for each stage, leading to a significant reduction in algorithmic complexity. Deng et al.[33] introduced an enhanced genetic algorithm featuring specialized operators for initialization, crossover, and mutation tailored to various gene types. This method is effective in providing good feasible solutions and finding optimal solutions when UAV resources are limited. Jia et al.[34] researched the two-stage collaborative multi-tasking problem with randomized speed and time window, and proposed a meta-heuristic algorithm based on improved genetic algorithm. The simulation results demonstrate that this algorithm surpasses other randomized search algorithms in both search efficiency and convergence speed. Considering the mission execution capability of UAVs and the probability of destruction of on-board munitions, Tian and Wang[45] established a task allocation optimization model based on the mission execution time and the attack benefit. Then they put forward a genetic algorithm based on multiple types of genetic coding to avoid the phenomenon of “deadlock”, which can quickly and efficiently solve the task allocation problem under multiple constraints.

### 2.2 Particle swarm algorithm

The particle swarm optimization (PSO) algorithm[46], initially introduced in 1995 by Kennedy and Eberhart[47], is a parallel meta-heuristic algorithm that emulates the collective foraging behaviors seen in birds, fish, and various organisms. It is employed to address optimization challenges. PSO boasts several advantages, including rapid convergence, high-quality solutions, and robustness when applied to multi-dimensional spatial function optimization and dynamic objective optimization. Therefore, it has been applied in many fields, such as multi-objective optimization, constrained optimization, signal processing, neural network training, and so on. The advantages of particle swarm algorithms in heterogeneous UAV tasking are collaborative search, balancing local and global search, and adapting to high-dimensional optimization and constraints, so it can provide efficient solutions to complex problems.

Wang et al.[1] utilized a multilayer coding strategy and a bound scheduling method to handle logical and physical restraints. They also introduced four optimization objectives to evaluate task allocation schemes. Subsequently, they present the improved multi-objective quantum particle swarm optimization (IMOQPSO) algorithm, which takes into account particle convergence and distribution. Additionally, it incorporates adaptive parameter control and a hybrid update mechanism. The method can handle the constraints more finely and improve the solution quality. In order to deal with the constraints of specified task order, time window and UAV heterogeneity, Zhang et al.[48] introduced an enhanced quantum particle swarm optimization (QPSO) algorithm that relies on a code-and-repair approach. This approach establishes a clear link between particle positions and the task assignment solution and it can solve problems more efficiently and stably. In addition, the algorithm can be used to solve the UAV task allocation problem in complex scenarios. In the work of Wang et al., they introduce introduce the knee point based co-evolution multi-objective particle swarm optimization (KnCMPSO) algorithm[21]. This approach utilizes a hybrid coding technique that relies on 3D matrices, along with an initialization method based on constraint processing. Additionally, it introduces learning strategies for inflection points, binary crossover methods, and local search strategies for interval perturbations, all aimed at enhancing the algorithm’s convergence and diversity. Drawing on coding methods, structural reorganization strategies, and co-evolutionary strategies for mission allocation and path planning, Wang et al.[49] introduced a co-evolution based mixed-variable multi-objective particle swarm optimization (C-MOPSO) algorithm, this algorithm has significant performance advantages over other algorithms using co-evolutionary strategies in terms of solution convergence and set diversity. Furthermore, they established a model for UAV cooperative multi-task allocation known as the M-CMTAP model.

### 2.3 Ant colony algorithm

The ant colony algorithm (ACO) is a bio-inspired optimization algorithm initially introduced in the early 1990s by Colorni et al.[50] It draws inspiration from the foraging behavior exhibited by ants. The algorithm adopts distributed parallel computing mechanism, which is robust and easy to be combined with other optimization algorithms, and thus receives wide attention. At first, ACO was mainly applied to solve the traveler’s problem (TSP) and achieved good results. As the algorithm has evolved, researchers have devised numerous enhancement strategies to elevate its performance. These improvements have expanded its applicability to diverse domains such as job scheduling, path planning, data mining, and more. These efforts have yielded a wealth of research outcomes and achievements[51, 52]. The model of the algorithm originates from the simulation of real ants’ foraging behavior, and guides the movement of individual ants through the release and perception of the pheromone, which ultimately realizes the ant colony searching for the optimal path under the action of self-organization. The advantages of ant colony algorithms in heterogeneous UAV task allocation are pheromone-guided balanced global local search, adaptive tuning and constraint processing. It is well-suited for tackling large-scale problems, can be parallelized effortlessly, and lends itself to efficient optimization for task allocation.

To enhance the model's realism, Gao et al.[53] categorized the heterogeneous objectives into point, line and area objectives. By grouping and arranging the characteristics of the model, they develop the grouping ant colony optimization algorithm and incorporated a negative feedback mechanism to expedite algorithm convergence, aiming to enhance the model's realism. Simulation results demonstrate the algorithm's growing advantage as the scale increases. Numerous studies have been conducted on ACO algorithms in the context of UAV task allocation problems[53–55]. However, existing theories either straightforwardly represent the original problem as a single-objective optimization issue or employ weighted sum techniques to convert the multi-objective optimization problem into a single-objective optimization problem. Chen et al.[56] introduced a multi-objective ant colony optimization (MOACO) algorithm featuring a novel pheromone update mechanism and four newly defined heuristic information parameters.Numerical experiments validate the algorithm's strengths, including faster convergence, higher solution quality, and increased diversity in the solutions it generates.

## 2.4 Clustering algorithm

Categorizing similar physical objects together is one of the earliest human activities, which is the original purpose of clustering. In 1984, Blashfield and Aldenderfer[57] proposed four major functions of cluster analysis: extending data categorization, exploring the concept of entity categorization, generating hypotheses, and testing categorization hypotheses based on real data sets. Cluster analysis has evolved alongside the progress in statistics, computer science, and artificial intelligence, finding widespread applications across various domains. Clustering algorithms are used to categorize tasks and reveal associations and differences between tasks, which can satisfy the correspondence between the number of mission clusters and the number of task-assigned UAVs. In UAV task allocation, distance clustering method is usually used. Clustering algorithms have significant advantages in heterogeneous UAV collaborative task allocation, optimizing resource matching through similarity analysis and task classification, reducing problem complexity, and adapting to dynamic environments in real time. The interpretability also gives it credibility in practical applications.

To appropriately address more realistic real-time dynamic scenarios, Tang et al.[58] integrated the concept of fuzzy C-means clustering into an ant colony optimization algorithm and introduced a reassignment strategy. Simulation results demonstrate that the proposed algorithm can effectively realize dynamic reallocation of multiple UAV tasks in dynamic emergent scenarios. To enhance the efficiency of task allocation in large-scale UAV swarms, Fu et al.[59] segmented the UAV swarms into multiple clusters based on task types, distances between UAVs, and other factors. This approach effectively transforms a large-scale problem into several interrelated small-scale problems. They also introduced a two-layer task assignment algorithm based on feature-weighted clustering, which proves to be advantageous for addressing large-scale task allocation problems, and is able to allocate tasks effectively and efficiently.

## 2.5 Reinforcement learning algorithm

Reinforcement learning (RL) has seen extensive application across various domains in recent years, thanks to the advancement of artificial intelligence technology[60, 61]. It is a machine learning approach whose goal is to maximize cumulative rewards by agents learning to take actions in interaction with their environment. It typically uses tables (Q-tables) or function approximation methods to represent policies or value functions. Deep reinforcement learning (DRL) is a branch of Reinforcement Learning that introduces deep neural networks to deal with high dimensional and complex state spaces to better solve real-world problems. DRL has demonstrated its powerful ability to learn and optimize decisions in several domains, such as problems like AlphaGo Zero[62] and Atari[63]. In addition, it is able to quickly find the best solution in discrete decision spaces with the advantages of speed and generalization, so it has a significant advantage in combinatorial optimization problems[64–67]. At present, a considerable number of researchers are employing reinforcement learning methods to address the challenge of cooperative task allocation in UAV systems.

With the advantages of dealing with uncertain environments and real-time implementability, RL offers an efficient solution for addressing the task allocation challenge among heterogeneous UAVs, particularly in the presence of environmental uncertainty. Zhao et al.[68] formalized the task allocation problem as a markov decision process (MDP) and introduced the fast task assignment (FTA) algorithm, which relies on Q-learning, neural network approximation, and prioritized experience replay, which is efficient in computation, adaptive, and able to deal with the effects of environmental uncertainty. This existing task allocation methods are mainly classified as centralized and distributed. Centralized methods require high real-time computation and communication for large-scale UAV systems, while distributed methods require global communication, which increases the burden of the system. In view of the limitations of past methods, Liu et al.[69] proposed a cooperative dynamic task allocation algorithm based on multi-intelligence body reinforcement learning. This approach achieves rapid response and resource reallocation for heterogeneous UAV systems through the creation of a coordination network and a Q-network. Simultaneously, it mitigates the computational overhead and enhances the scalability of the system. Yue et al.[70] proposed a hierarchical multi-intelligent body reinforcement learning approach aimed at solving the cooperative decision-making problem of heterogeneous UAV swarms in large-scale, uncertain scenarios. The method introduces hierarchical reinforcement learning and multi-intelligent body reinforcement learning algorithms, and utilizes neural networks to automatically extract important features of complex high-dimensional combat scenarios. In real-world combat environments, combat situations are usually more urgent, so it is important to make optimal decisions in the most limited time. Based on reinforcement learning, Zhu and Fang[71] proposed an improved Q-learning algorithm. This method improves exploration efficiency, increases the possibility of obtaining better solutions, and avoids falling into a local optimum by accepting worse actions in random exploration and eliminating the probability of future actions that consistently produce worse returns.

## 2.6 Other algorithms

Beyond the algorithms mentioned earlier, there exist numerous other methods designed to address the challenge of task assignment in heterogeneous UAV cooperative scenarios.

In the study by Wang et al.[72], they formulated a multi-UAV, multi-mission planning model that includes time windows. They also enhanced the taboo search algorithm, thus improving its optimization capabilities and increasing the likelihood of obtaining superior global optimal solutions. Wang et al.[73] used a heuristic-based hybrid algorithm to give mission planning for a fleet of fixed-wing heterogeneous UAVs to perform different missions at different locations in different time windows, and numerical experiments show that the algorithm can effectively handle large-scale problems. Chen et al.[74] tackled the task assignment problem under constraints related to task types and UAV sensor limitations. They formulated the problem as the multiple time window based durbin travelling salesman problem (MTWDTSP) and solved it using a modified multi-objective symbiotic organism search (MOSOS) algorithm. The algorithm exhibit improved optimality and efficiency in generating assignment results, enhancing the probability of converging to the optimal solution. Luo et al.[75] presented a solution to maximize completion time and minimize total task time by considering the function or function level of UAVs and time constraints. They introduced a multi-swarm fruit fly optimization algorithm with a two-strategy switching mechanism. The results indicate that the algorithm possesses enhanced global search capabilities and offers improved efficiency and stability. Chen et al.[76] introduced a chaotic wolf pack algorithm based on an enhanced stochastic fractal search (MSFS-CWPA) to address the task assignment problem, considering the performance characteristics of specific payloads. This approach exhibits superior convergence accuracy and robustness. Liu et al.[77] introduced the fruit picking technique into the nearest neighbor method with the shortest neighbor distance as the index, and then proposed the orchard picking algorithm (OPA) which can quickly give the optimal sequence of missions. Simulation results show that this algorithm is flexible, robust and scalable. Within the constraints of resources, effective task execution range, task avoidance and task priority, Fan et al.[78] proposed a discrete adaptive search whale optimization algorithm. As this algorithm first utilizes an obstacle avoidance distance estimation method, then updates based on intersection points and introduces a search intensity adaptive mechanism, so it can effectively solve the discrete problem while reducing the computational complexity. For the complex constraints such as specified task sequences and time windows, Zhang et al.[79] introduced an enhanced simulated annealing particle swarm optimization (SAPSO) algorithm and establish the connection between particle swarms and feasible task allocation schemes. Cui et al.[80] introduced an opposition-based learning parameter-adjusting harmony search algorithm to address the task allocation problem while taking into account constraints related to heterogeneous load and task cost.

In summary, with the increasing complexity of application environments and mission requirements, a single UAV is no longer able to meet the requirements due to the limitation of UAV size and capability. Multiple heterogeneous UAVs working together are getting more and more attention due to their higher team performance. However, rationally coordinating multiple UAVs for multi-task allocation planning is critical. As the scale of UAVs and objectives grows, along with an increase in constraints, the solution space exponentially expands, leading to a rise in computational complexity. To tackle this challenge, intelligent optimization algorithms have found extensive application in task allocation problems due to their conceptual simplicity, enhanced stability, and increased efficiency. Table 2 presents the performance indicators such as robustness and convergence speed of UAV swarm tasking algorithms and compares the algorithms based on these indicators.

## 3 Research Prospect

Advancements in technology are continually elevating the significance of UAVs in both civil aviation and military domains. UAVs are increasingly capable of performing diverse tasks, including target surveillance, weather monitoring, and more. However, as the number and complexity of tasks increase, the limitations of a single UAV become obvious, which prompts multi-UAV cooperative work to become a research hotspot. Multi-UAV autonomous control encompasses various facets, including task assignment, path planning, and formation control. Cooperative task assignment stands out as a pivotal factor in mission success. In recent years, researchers have extensively studied multi-UAV cooperative task allocation, and the field has been receiving increasing attention, which not only brings opportunities but also significant challenges.

There are several challenges to collaborative UAV tasking. Firstly, the heterogeneity of UAVs is a major challenge, as different types and models of UAVs have different flight performance, load capacity and endurance. This heterogeneity complicates the tasking problem, and thus requires rational tasking to maximize the use of the characteristics of various UAVs.

Secondly, the multi-mission multi-target problem needs to be solved. Typically, limited UAV resources need to be allocated among multiple tasks, which may have different priorities and

**Table 2 Performance comparison of common intelligent optimization algorithms.**

| Indicator | Performance | | | |
|---|---|---|---|---|
| | GA | PSO | AOC | Clustering algorithm |
| Dynamism | Moderate | Strong | Strong | Strong |
| Robustness | Strong | Strong | Strong | Weak |
| Fault tolerance | Strong | Moderate | Strong | Moderate |
| Accuracy | Moderate | Moderate | Moderate | Moderate |
| Applicable scale | Moderate | Large | Large | Moderate |
| Convergence speed | Fast | Fast | Fast | Fast |
| Real-time | Weak | Weak | Weak | Fast |
| Reliability | High | Low | High | High |

objectives. The task allocation problem needs to strike a balance between multiple objectives, such as maximizing the number of tasks to be completed, minimizing the total cost, or maximizing the coverage. In addition, the large-scale task allocation problem involves a large number of UAVs and tasks, which increases the computational complexity. Meanwhile, UAVs are subject to resource constraints during flight, such as fuel, battery life, and payload capacity, which also need to be considered in task allocation.

Thirdly, the task allocation must also satisfy various task constraints, including time window, geographic location, and other constraints. Simultaneously, tasks and environmental conditions can evolve over time, necessitating real-time adjustments in task allocation to adapt to these changes. Many uncertainties such as weather, wind speed, and target location also need to be taken into account to ensure that the task assignment algorithms are able to adapt as well as adjust to uncertain situations.

In addition, communication and cooperative control, privacy and security issues are also two important challenges. The former is due to the fact that effective communication and cooperative control between UAVs may be affected by factors such as communication delays, bandwidth limitations, data loss, and collaborative decision-making. The latter is because tasking involves the transmission of sensitive information, such as UAV and mission location information and sensor data. Ensuring the privacy and security of this information is of paramount importance in the task allocation process.

Finally, learning-based algorithms adjust strategies by learning from experience, analyzing large amounts of data quickly and giving tasking decisions efficiently, which can meet the demands of dynamic operational environments, continuously optimize mission execution, and improve the accuracy and quality of mission execution. Such algorithms, especially reinforcement learning and deep learning methods, can coordinate the operation of large-scale UAV swarms more efficiently and realize the scaled execution of complex tasks. In order to improve the autonomy, efficiency and adaptability of UAV swarms, we can improve the robustness and fault tolerance of the algorithms, the interpretability of the decision-making process, and the security of the learning model in the further research to address the increasingly complex application requirements.

## 4 Conclusion

Heterogeneous unmanned aerial vehicle (UAV) swarms have attracted extensive interest from the domestic and international research communities due to their excellent flexibility, diverse mission capabilities, and wide range of application prospects. The objective of this paper is to delve into the challenge of cooperative task allocation within heterogeneous UAV swarms and explore the application of artificial intelligence in addressing this issue. The review introduces the wide application of artificial intelligence algorithms in UAV swarm mission planning as well as analyzes the advantages and disadvantages of these algorithms in multi-UAV swarm mission planning. By delving into these key techniques and their applications, this paper indicates future research directions and challenges. The review highlights the extensive utilization of artificial intelligence algorithms in UAV swarm mission planning and provides an analysis of the strengths and weaknesses of these algorithms in the context of multi-UAV swarm mission planning.

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