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Cooperative Multiple Task Assignment of Heterogeneous UAVs Using a Modified Genetic Algorithm with Multi-type-gene Chromosome Encoding Strategy

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Abstract

The cooperative multiple task assignment problem (CMTAP) of heterogeneous fixed-wing unmanned aerial vehicles (UAVs) performing the Suppression of Enemy Air Defense (SEAD) mission against multiple ground stationary targets is studied in this paper. The CMTAP is a NP-hard combinatorial optimization problem, which faces many challenges like problem scale, heterogeneity of UAVs (different capability and maneuverability), task coupling and task precedence constraints. To address this issue, we proposed a modified genetic algorithm (GA) with multi-type-gene chromosome encoding strategy. Firstly, the multi-type-gene encoding scheme is raised to generate feasible chromosomes that satisfy the UAV capability, task coupling and task precedence constraints. Then, Dubins car model is adopted to calculate the mission execution time (objective function of CMTAP model) of each chromosome, and make each chromosome conform to the UAV maneuverability constraint. To balance the searching ability of algorithm and the diversity of population, we raise the modified crossover operator and multiple mutation operators according to the multi-type-gene chromosome encoding. The simulation results demonstrate that the modified GA has better optimization performance compared with random search method, ant colony optimization method and particle search optimization method.

Keywords Unmanned aerial vehicles · Cooperative task assignment · Genetic algorithm · Multi-type-gene chromosome encoding · Dubins car model

1 Introduction

Unmanned aerial vehicle (UAV) has the advantages of low cost, zero casualty, strong mobility and low detectability, which is capable of performing boring, harsh, dangerous and hidden tasks in complex battlefield [1, 2]. Due to limit capacity, single UAV cannot realize multi-dimensional and extensive coverage of mission area. Thus, the development of multi-UAV cooperation is essential to improve the efficiency of mission completion [3]. This paper concentrates on cooperative task assignment that allocates multiple heterogeneous fix-wing UAVs to perform Suppression of Enemy Air Defense (SEAD) mission on multiple ground stationary targets.

The cooperative multiple task assignment problem (CMTAP) in this paper has two characteristics. Firstly, UAV team is composed of heterogeneous fix-wing UAVs, including the surveillance UAV, combat UAV and munition UAV. The heterogeneity of UAVs reflects on different capability (ability to perform certain tasks, e.g., munition UAV can only execute attack task) and different maneuverability (cruise speed and turning radius). Secondly, there are strict task coupling and task precedence constraints. In SEAD scenario, UAV team is required to perform three tasks (classify, attack and verify) against targets. The attack task can only be performed after completing classify task, and verify task can only be performed after target is attacked.

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Some researches on the cooperative task assignment only focus on single-type task [4–6] or homogeneous UAVs [4–8]. Due to the lack consideration on multi-type tasks, these approaches cannot be directly applied in SEAD mission. Then, multiple combat UAVs are considered to perform SEAD mission on multiple targets in [9–12]. These papers only consider the homogeneous UAVs, which ignore the emergence of heterogeneous UAVs in actual aerial battlefield. Considering UAVs' maneuvering performance, UAVs' heterogeneous capabilities, task coupling and task precedence constraints, CMTAP is a strongly NP-hard combinatorial optimization problem [13]. On the one hand, with the increasing of CMTAP model scale, the number of possible solutions rises exponentially. Analytic methods like mix integer linear program [14–16], decision tree [17, 18] face prohibitive computational complexity when handling large, complex CMTAP scenarios [13]. On the other hand, the UAV heterogeneity, task coupling and task precedence constraints brings significant complexity to CMTAP model. The enumeration operation of analytic methods will produce many infeasible solutions and make the algorithm uneasy to converge. Rasmussen and Shima [10] revealed that obtaining a feasible solution in an allotted time period is more desirable than waiting until the optimal solution is reached in practical application. Thus, various researches focus on applying intelligent optimization methods to CMTAP model. Taking the task precedence and coordination into account, [19, 20] developed GA to solve the CMTAP model. Shima et al. [19] and Darrah et al. [20] revealed that GA can efficiently solve the assignment problem without resolving to the computational complexity of analytic methods. Yao et al. [21] designed a GA chromosome encoding method based on task sequence. However, the method uses binary matrixes to represent chromosomes, which leads to inevitably computation complexity in large scenarios. By introducing the Dubins car model [23–25], [22] raised the integrated scheme of task assignment and motion planning based on GA and graph representation. Then, a modified GA based on multi-type genes and mirror representation is put forward in [26]. However, the presented method in [26] may produce deadlock chromosomes that violate the task coupling and task precedence constraints. Thus, [26] developed a graph-based method to solve the potential deadlock. It's obvious that handling the deadlock problem increases the computational complexity. Besides, [27] presented a hybrid gravitation searching algorithm-genetic algorithm. The segment encode scheme of the hybrid algorithm is composed of task allocation segment and task sequencing segment, in which the length of chromosome is twice as that of [26].

In this paper, the proposed GA with multi-type-gene chromosome encoding strategy is designed to produce feasible solution for CMTAP model. Firstly, the raised encoding scheme guarantees to produce feasible and deadlock-free chromosomes that satisfy the UAV heterogeneity, task coupling and task precedence constraints. After that, Dubins car model is used to simulate the UAV path that conforms to maneuverability constraint and calculate the objective function of GA (defined as the mission execution time of UAV team). According to the characteristics of chromosome encoding method, the corresponding population initialization, crossover and mutation operators are then designed to search for the optimization solution. In this paper, we designed five mutation operators to overcome the poor local search ability and precocious performance of GA.

The rest of this paper is arranged as follows. Section 2 presents the CMTAP model. Section 3 elaborates the modified GA, including the multi-type-gene chromosome encoding strategy, population initialization and genetic operators. Simulations and analyses are shown in Section 4. At last, Section 5 concludes the paper.

2 Problem Formulation

Based on the CMTAP model in [12, 17], this paper addresses the scenario of assigning multiple heterogeneous fixed-wing UAVs to execute SEAD mission against multiple ground stationary targets under the following assumptions.

1) Each UAV has its fixed altitude. That is, each UAV flies at different altitude and different UAVs have no collisions.
2) There is no limit to fuel and weapon system in UAV team.
3) UAVs take off from the same base at the same time.
4) There is no requirement on the task execution angle. An UAV can perform a task by passing directly over a target.
5) There is no priority or time window requirements on the targets.

The main symbols used in this section are shown in Table 1.

2.1 Targets and Tasks

Suppose that there are N_T stationary ground targets with known positions, the set of targets is

$$\mathbf{T} = \{T_1, T_2, \ldots, T_{N_T}\} \tag{1}$$

The set of tasks to be performed on each target is

$$M_T = \{C, A, V\} \tag{2}$$

where C, A, V separately represent the classify, attack and verify tasks.

Table 1 Nomenclature

	Symbol	Description
	$\mathbf{T}$	**set of targets**
Target-related	N_T	number of targets
	$\mathbf{M_T}$	**set of tasks to be performed on each target**
	N_M	total number of tasks to be performed on all targets
	$\mathbf{U}$	**set of UAVs**
	N_U	number of UAVs
UAV-related	$\mathbf{U_S}$	**set of UAVs which can perform surveillance task**
	$\mathbf{U_A}$	**set of UAVs which can perform attack task**
	$[r_1, r_2, \dots, r_{N_U}]$	cruise speed of UAVs
	$[v_1, v_2, \dots, v_{N_U}]$	turning radius of UAVs
	t_{U_k}	task execution time of UAV U_k
Model-related	$X_{(q_i,q_j)}^{U_k,m}$	binary decision variable of CMTAP model
	$d_{(q_i,q_j)}^{U_k}$	Dubins path length of UAV U_k flying from location q_i to q_j

Bold entries represent the definitions of UAV set, target set, and task set

Apparently, there are $\|M_T\| = 3$ tasks that need to be executed on each target. In the SEAD scenario, the total number of tasks to be performed on all targets is $N_M = N_T \cdot \|M_T\| = 3N_T$. The execution of three tasks follows strict task coupling and task precedence constraints. The A task can only be executed after completing C task, and V task can only be performed after target is attacked.

2.2 UAVs

Assume that there are N_U heterogeneous fix-wing UAVs in the UAV team, the set of UAV is defined as

$$\mathbf{U} = \{U_1, U_2, \dots, U_{N_U}\} \tag{3}$$

The heterogeneity of UAVs in this paper reflects on different capability and different maneuverability.

Firstly, the UAV team has surveillance UAV, combat UAV and munition UAV. The capabilities of different UAVs are exhibited in Table 2. It is obvious in Table 2 that the surveillance UAV can perform surveillance tasks $\{C, V\}$, the munition UAV can perform attack task $\{A\}$, and the combat UAV can perform all tasks $\{C, A, V\}$.

Based on Table 2, we define $\mathbf{U}_S, \mathbf{U}_A$ to separately represent the set of UAVs that can perform surveillance task, and the set of UAVs that can perform attack task.

$$\mathbf{U}_S = \Big\{U_1, U_2, \dots, U_{N_{U_S}}, U_{N_{N_S}+1}, U_{N_{N_S}+2}, \dots, U_{N_{N_S}+N_{U_C}}\Big\} \tag{4}$$

$$\mathbf{U}_A = \Big\{U_1, U_2, \dots, U_{N_{U_M}}, U_{N_{N_M}+1}, U_{N_{N_M}+2}, \dots, U_{N_{U_M}+N_{U_C}}\Big\} \tag{5}$$

where $N_{U_S}, N_{U_C}, N_{U_M}$ respectively represent the number of surveillance UAVs, the number of combat UAVs and the number of munition UAVs.

Obviously, the following equations are satisfied.

$$\mathbf{U} = \mathbf{U}_S \cup \mathbf{U}_A \tag{6}$$

$$N_U = N_{U_S} + N_{U_C} + N_{U_M} \tag{7}$$

Then, the cruise speed $[v_1, v_2, \dots, v_{N_U}]$ and turning radius $[r_1, r_2, \dots, r_{N_U}]$ of UAVs reflect their different maneuverabilities. Dubins car model solves the shortest path problem from one point with given orientation to a second point with given orientation [25]. Thus, Dubins car model is introduced to generate the shortest UAV path between configurations $(x_{start}, y_{start}, \varphi_{start})$ to $(x_{end}, y_{end}, \varphi_{end})$. Given start and end configurations, the Dubins paths is determined [26]. Dubins path must be one of the six combinations of line segments and curvature arcs: $\{LSL, RSR, RSR, RSL, LRL, RLR\}$, where R is the clockwise turn, L is the counterclockwise turn, and S is the straight line [23–25].

2.3 CMTAP Model

The purpose of CMTAP model is to allocate multiple heterogeneous fix-wing UAVs to perform SEAD mission on multiple ground stationary targets. In this paper, we design the objective function of CMTAP model as to minimize the mission execution time of UAV team.

$$\min J = \max_{U_k \in \mathbf{U}} t_{U_k} \tag{8}$$

Table 2 Capabilities of different UAVs

UAV type	Capability	Available tasks
Surveillance	Surveillance	$\{C, V\}$
Combat	Surveillance, Attack	$\{C, A, V\}$
Munition	Attack	$\{A\}$

where t_{U_k} is the task execution time of UAV U_k performing its assigned tasks.

$$t_{U_k} = \sum_{i=1}^{N_V} \sum_{j=1}^{N_T} \sum_{m=1}^{3} \{\frac{X_{(q_i,q_j)}^{U_k,m} d_{(q_i,q_j)}^{U_k}}{v_k}\} \tag{9}$$

where $X_{(q_i,q_j)}^{U_k,m} \in \{0, 1\}$ is the binary decision variable. $X_{(q_i,q_j)}^{U_k,m} = 1$ means that UAV U_k flys from configuration q_i to q_j to perform task m on target T_j, vice versa. $d_{(q_i,q_j)}^{U_k}$ is the Dubins path length of UAV U_k flying from configuration q_i to configuration q_j. q_i, q_j separately represent the last and current configurations of UAV U_k. $N_V = N_U + N_T$ represents all possible configurations of UAVs during the mission, including their take-off configurations and possible configurations on targets.

In Eq. 9, the term inside the parenthesis represents the task execution time of UAV U_k when executing task m of target j. Thus, t_{U_k} defines the task execution time of UAV U_k performing all assigned tasks.

Two constraints of the CMTAP model are

$$\sum_{k=1}^{N_U} \sum_{i=1}^{N_V} \sum_{m=1}^{3} X_{(q_i,q_j)}^{U_k,m} = \|M_T\|, \forall j \in \mathbf{T} \tag{10}$$

$$t_{T_j}^C < t_{T_j}^A < t_{T_j}^V, \forall j \in \mathbf{T} \tag{11}$$

Equation 10 shows that for each target, $\|M_T\|$ tasks must be performed once. Equation 11 reflects that for each target, $\|M_T\|$ tasks need to be executed in order. Thus, Eqs. 10, 11 describe the task coupling and task precedence constraints.

Referring to Table 2, the third constraint of CMTAP model is that the capability of assigned UAV U_k should have the required capability of assigned task m.

3 The Proposed GA

To solve the CMTAP model in this paper, we proposed a modified GA. Firstly, the multi-type-gene chromosome encoding strategy is raised to generate feasible individuals that satisfy the UAV heterogeneity, task coupling and task precedence constraints. Based on Dubins car model, the task execution time of each UAV in Eq. 9 can be calculated, and then the objective function of CMTAP model in Eq. 8 can be derived. According to the unique chromosome encoding strategy, we designed a feasible population initialization to generate valid and deadlock-free chromosomes. Besides, the crossover operator and multiple mutation operators are put forward.

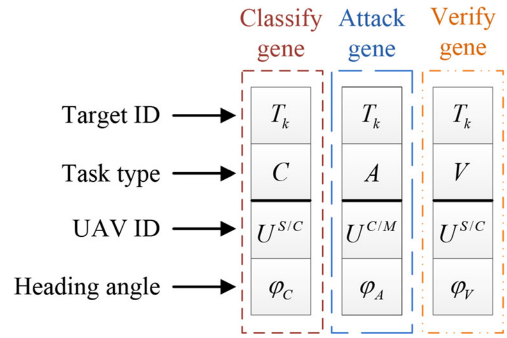


Fig. 1 Multi-type genes

3.1 Multi-type-gene Chromosome Encoding Strategy

Chromosome encoding is the premise of GA. We firstly raise the multi-type-gene concept. Taking target T_k as an example, Fig. 1 describes the multi-type-gene strategy.

Classify, attack and verify genes of target T_k are shown in Fig. 1. Each gene shows a UAV configuration of the task assignment. For example, the classify gene shows that UAV $U^{S/C}$ performs C task on target T_k with heading angle φ_C. We can see from classify gene that only UAV with surveillance capability can perform the C task. Thus, the third constraint of CMTAP model is realized.

Based on the multi-type-gene strategy, we design the proposed chromosome encoding scheme. An example is used to illustrate the multi-type-gene chromosome encoding scheme.

Example 1 Assuming that the UAV team $\mathbf{U} = \{U_1^S, U_2^C, U_3^M\}$ from the same base needs to perform SEAD mission on two targets $\mathbf{T} = \{T_1, T_2\}$. The cruise speed vector and turning radius vector are $[v_1, v_2, v_3] = [70, 80, 70]$ m/s $[r_1, r_2, r_3] = [200, 250, 200]$ m, the initial heading angles of UAVs are $[\varphi_1^0, \varphi_2^0, \varphi_3^0] = [0°, 45°, 90°]$. Introducing the task execution order as the 1^{st} row, one feasible chromosome using the multi-type-gene encoding scheme is shown in Fig. 2.

We can see from Fig. 2 that the chromosome is composed of $N_M = N_T \cdot \|M_T\| = 6$ genes. The number of genes

Order →	1	2	3	4	5	6
Target ID →	T_1	T_1	T_2	T_2	T_2	T_1
Task type →	C	A	C	A	V	V
UAV ID →	U_1^S	U_2^C	U_2^C	U_3^M	U_1^S	U_2^C
Heading angle →	296°	354°	208°	292°	258°	190°

Fig. 2 Multi-type-gene chromosome

in chromosome equals to the number of all tasks, which shows that exactly $\|M_T\| = 3$ tasks are performed on each target. Thus, the first constraint of CMTAP model in Eq. 10 is established.

Then, we introduce two transformations of the multi-type-gene chromosome. The target-order and UAV-order chromosomes are exhibited in Fig. 3.

Arrange the chromosome in Fig. 2 by target ID and task type, we can derive the target-order chromosome in Fig. 3a. Taking target T_1 in Fig. 3a as an example, the execution of three tasks C, A, V follows the task precedence constraint in Eq. 11. Hence, the second constraint of CMTAP model is achieved.

According to above analyses, the multi-type-gene chromosome in Fig. 2 satisfies three constraints of CMTAP model.

Arrange the chromosome by UAV ID and task execution order, we can derive the UAV-order chromosome in Fig. 3. The UAV-order chromosome gives the configurations of UAVs during the mission: U_1^S classifies target T_1 and then verifies target T_2 after it has been attacked by U_3^M. U_2^C attacks target T_1 after it has been classified, flies to target T_2 to perform classify task, and then flies to target T_1 to verify the target T_1.

$$U_1^S : (Base, \varphi_1^0) \rightarrow (T_1^C, 296°) \rightarrow (T_2^V, 258°) \tag{12}$$

$$U_2^C : (Base, \varphi_2^0) \rightarrow (T_1^A, 354°) \rightarrow (T_2^C, 208°) \rightarrow (T_1^V, 190°) \tag{13}$$

$$U_3^M : (Base, \varphi_3^0) \rightarrow (T_2^A, 292°) \tag{14}$$

Based on the assigned configurations of UAVs, Dubins car model is used to generate their Dubins paths (shown in Fig. 4).

Dividing the Dubins paths of UAVs by their cruise speeds, we can obtain the task execution times of UAVs based on Eq. 9.

$$[t_{U_1}, t_{U_2}, t_{U_3}] = [120.3473, 162.4719, 118.0666]s$$

Then, the objective value of the chromosome can be derived based on Eq. 8.

$$J = \max_{U_k \in \mathbf{U}} t_{U_k} = 162.4719s \tag{15}$$

The objective function and three constraints of CMTAP model are separately described by the proposed multi-type-gene chromosome encoding scheme. Therefore, the proposed chromosome encoding method is feasible.

Original chromosome is obtained by arranging the target-order/UAV-order chromosome based on the task execution order. Thus, chromosome, target-order chromosome and UAV-order chromosome can be mutual transformed.

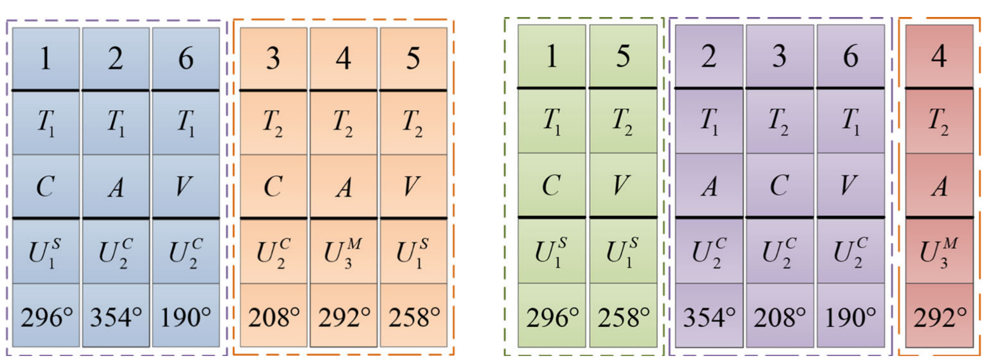
3.2 Population Initialization

Based on the multi-type-gene chromosome encoding strategy, the population initialization process (shown in Algorithm 1) generates N_p (N_p is the population size) feasible chromosomes as the initial population.

Algorithm 1 Population initialization.

Input Required population size: N_p; Target-related: $\mathbf{T}$, N_T, $\|M_T\|$, N_M; UAV-related: $\mathbf{U}$, $\mathbf{U}_S$, $\mathbf{U}_A$.
Output N_p feasible chromosomes.

Step 1. Create a $5 \times N_M$ all-zero matrix to represent the chromosome.
Step 2. Generate the task execution order from 1 to N_M as the 1^{st} row of chromosome.
Step 3. Randomly arrange N_T tasks $\|M_T\|$ times as the 2^{nd} row of chromosome.
Step 4. For each target, add the tasks C, A, V of each target successively as the 3^{rd} row of chromosome.
Step 5. According to the required task type in the 3^{rd} row, randomly select capable UAV from the corresponding UAV set $\mathbf{U}_S/\mathbf{U}_A$ as its assigned UAV in the 4^{th} row.
Step 6. Randomly generate the heading angle as the 5^{th} row of chromosome.
Step 7. Repeat Steps 1.-6. N_p times to get the initial population.



(a) Target-order chromosome (b) UAV-order chromosome

Fig. 3 Two transformations of chromosome

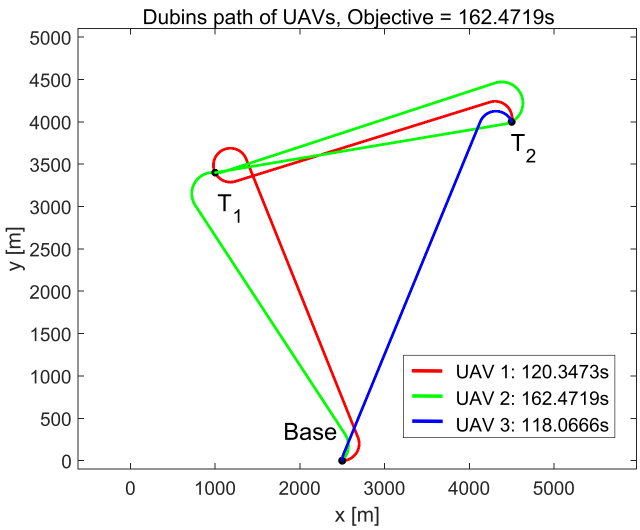


Fig. 4 Dubins paths of UAVs

In Algorithm 1, step 4. ensures that exactly three tasks C, A, V on each target are performed and tasks C, A, V of each target are performed in sequence. That is, task coupling and task precedence constraints in Eqs. 10, 11 are satisfied. Step 5. shows that in each gene, the assigned UAV has corresponding capability to the required task type. That is, the third constraint of CMTAP model is established. Therefore, the population initialization in Algorithm 1 generates N_p feasible chromosomes.

3.3 Genetic Operators

We utilize selection, elitism, crossover and mutation operators in this paper. The roulette wheel method is applied as the selection operator to randomly select the parent chromosomes. The roulette wheel method ensures that the individual with higher fitness value has bigger possibility to be chosen. Elitism operator directly preserves the predetermined N_e parent chromosomes with the highest fitness values into the offspring population. Elitism strategy can improve the convergence speed of the proposed GA through reserving the optimal individuals. In this paper, crossover and mutation operators are modified according to the proposed chromosome encoding strategy.

3.3.1 Crossover Operator

In the proposed GA, there are $N_{cr} < N_p - N_e$ offspring individuals generated through the crossover process. The crossover operator can improve the global searching ability of the proposed GA through the information exchange among the population. In the crossover operation, two selected parent chromosomes exchange their gene information to create two new chromosomes as the offspring individuals. Notably, the objective value of chromosome is calculated based on the accumulation of Dubins paths between assigned configurations. It is important to reserve the good continuous configurations of parent chromosomes in the crossover operation. Therefore, we use the two-point crossover operator to exchange the continuous configurations between two parent chromosomes. The crossover process is realized by Algorithm 2.

Algorithm 2 Crossover operation.

Input N_{cr}, N_p.
Output N_{cr} offspring chromosomes.

Step 1. Randomly select two parent chromosomes via the roulette wheel method, and transform two parent chromosomes to target-order parent chromosomes.
Step 2. Randomly choose two crossover sites, exchange the gene information of two target-order parent chromosomes between two crossover sites to generate two target-order offspring chromosomes.
Step 3. Transform two target-order offspring chromosomes back to offspring chromosomes.
Step 4. Repeat Steps 1.-3. $N_{cr}/2$ times to complete the crossover operation.

The crossover process of **Example** (shown in Section 3.1) is illustrated in Fig. 5.

Notably, the information exchange in step 2. only exchanges the assigned UAV and its heading angle. On the one hand, the 2^{nd} and 3^{rd} rows of all target-order chromosomes are the same. Only exchange the 4^{th} and 5^{th} rows will reduce the computation complexity during the crossover operation. On the other hand, the task execution order in the 1^{st} row is not involved in the crossover process because it guarantees valid transformation between chromosome and target-order chromosome without violating the task precedence constraint. As long as the parent chromosomes satisfy the CMTAP constraints on UAV heterogeneity, task coupling and task precedence, the offspring chromosomes will follow the same constraints. Thus, the crossover operator generates feasible offspring chromosomes.

3.3.2 Mutation Operators

In the proposed GA, there are $N_{mu} = N_p - N_e - N_{cr}$ offspring individuals that are generated through the mutation process. The mutation operator can overcome the premature phenomenon of crossover process and enhance the diversity of population. The mutation process (shown in Algorithm 3) changes one or more genes of the probabilistically selected parent chromosome to generate the offspring chromosomes.

Algorithm 3 Mutation operation.

Input N_{mu}, N_p.
Output N_{mu} offspring chromosomes.

Step 1. Randomly select the parent chromosome via the roulette wheel method, and transform the parent chromosome to target-order parent chromosome.
Step 2. Randomly choose the mutation site, apply one mutation way to generate the target-order offspring chromosome.
Step 3. Transform the target-order offspring chromosomes back to offspring chromosome.
Step 4. Repeat Steps 1.-3. N_{mu} times to complete the mutation operation.

To enhance the diversity of GA population, we proposed five mutation ways to change the gene(s) of the target-based parent chromosome in step 2.: 1) mutate the assigned UAV of the mutation site; 2) mutate the heading angle of the mutation site; 3) mutate the assigned UAV of the chosen target according to $\|U_{type}\| - x$, where x is the assigned UAV of the chosen target, and $\|U_{type}\|$ is the number of UAVs that have the same capability of x; 4) randomly choose two targets and select a mutation task, exchange the assigned UAV and the heading angle of the mutation task between two targets; 5) randomly choose two targets, and exchange the assigned UAV and the heading angle of all tasks between two targets.

In the **Example** shown in Section 3.1, $\mathbf{U}_S = \{U_1^S, U_2^C\}, \mathbf{U}_A = \{U_2^C, U_3^M\}$ separately represent the UAV sets which can perform surveillance task and attack task. The five mutation ways of **Example** are illustrated in Fig. 6.

Taking the mutation of assigned UAV in Fig. 6 as an example, U_2^C is change to another UAV with the same capability, That is, $\mathbf{U}_A \setminus \{U_2^C\} = \{U_3^M\}$. It's easy to check in Fig. 6 that these five mutation ways will not make the offspring chromosome violate the constraints on UAV heterogeneity, task coupling and task precedence. Thus, the offspring chromosomes after mutation process are feasible.

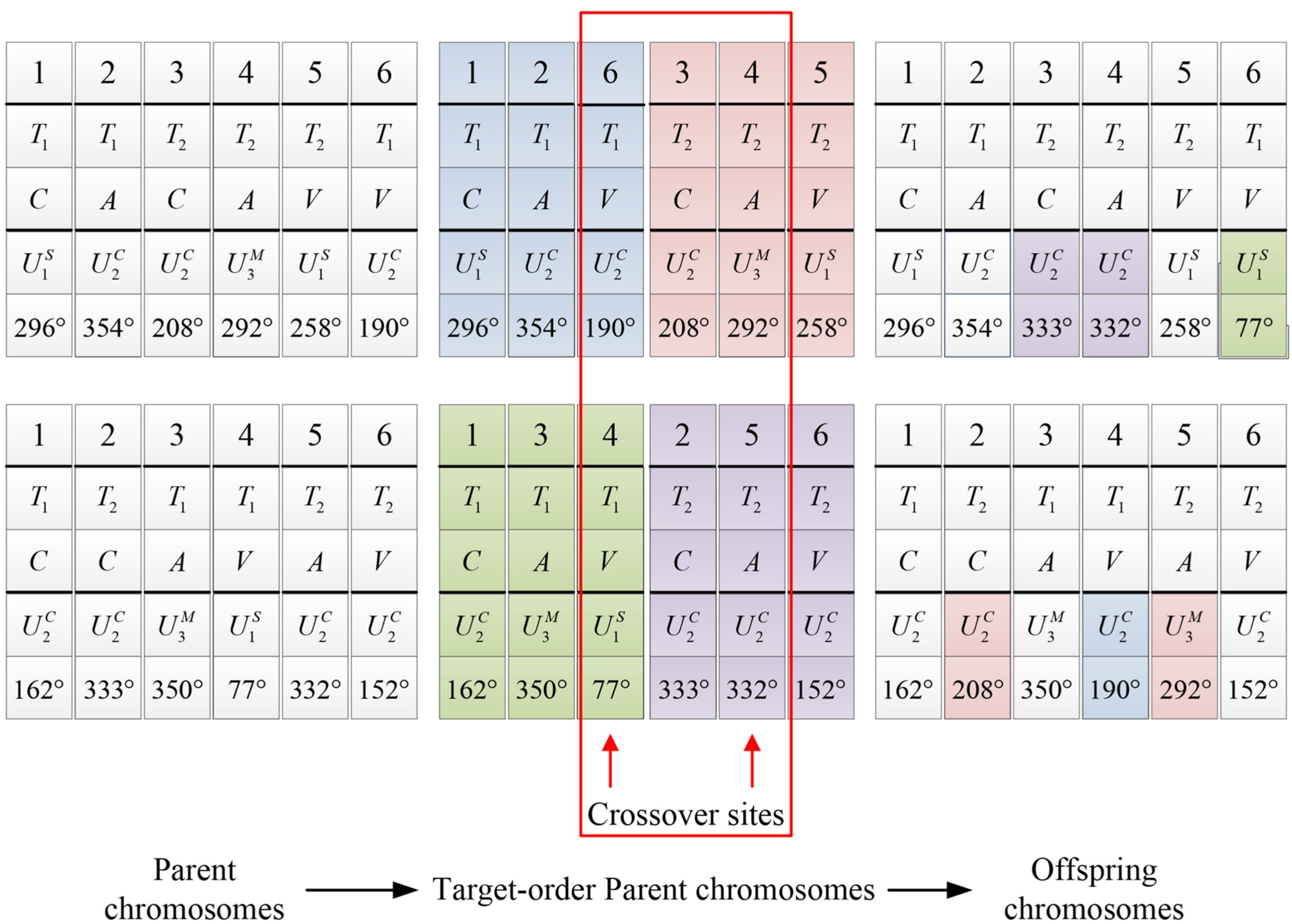


Fig. 5 Crossover operation of Example

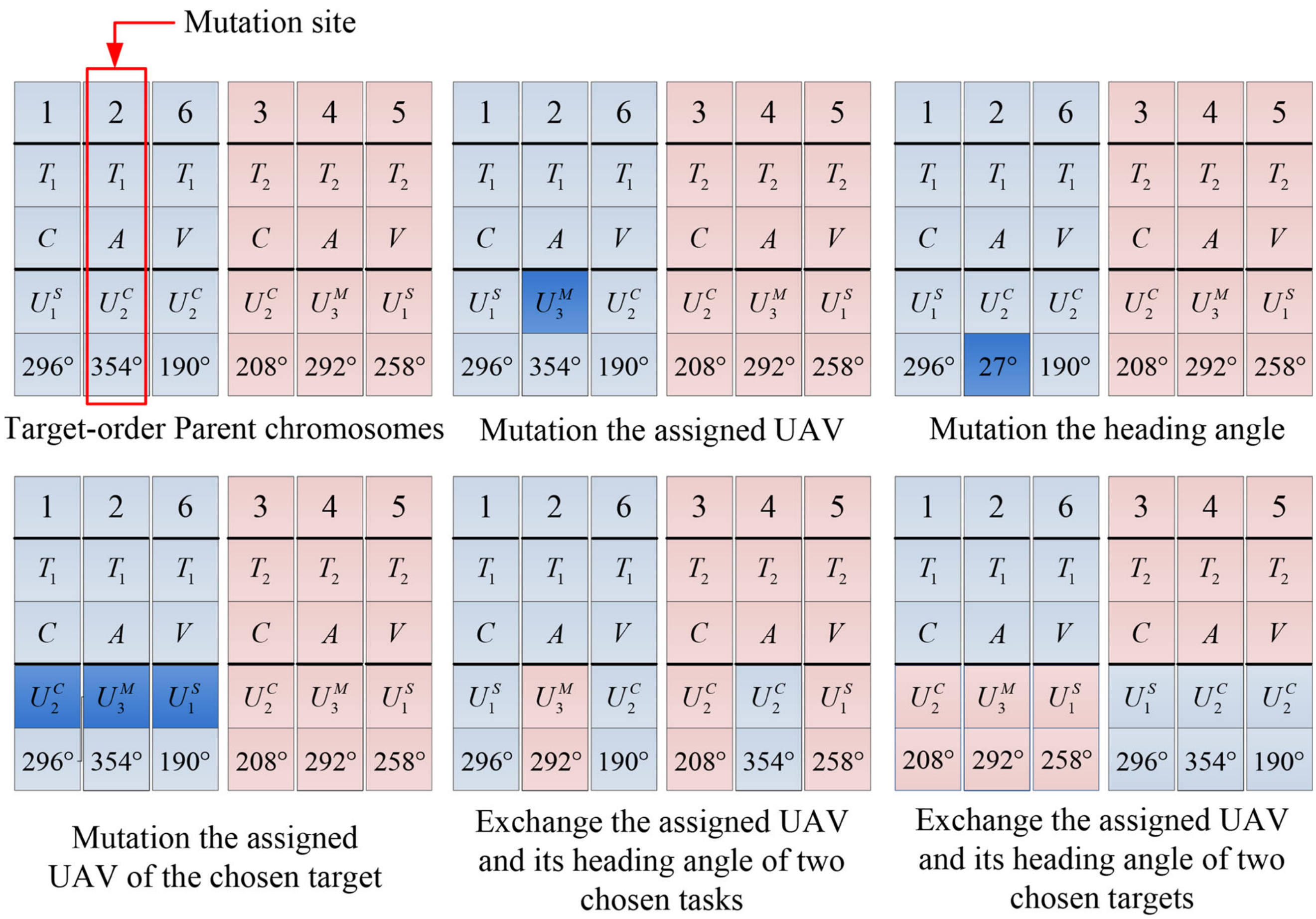


Fig. 6 Crossover operation of Example

Table 3 Simulation scenarios

Scenarios	Position of targets and initial status of UAVs
3 UAVs against 4 targets	Position of base $[2500, 0]m$
	Position of targets $[800, 3200; 2800, 4200; 4000, 2000; 1000, 760]m$
	Cruise speed vector of UAVs $[v_1, v_2, v_3] = [70, 80, 70]m/s$
	Turning radius vector of UAVs $[r_1, r_2, r_3] = [200, 250, 200]m$
	Initial heading angles of UAVs $[\varphi_1, \varphi_2, \varphi_3] = [0°, 45°, 90°]$
5 UAVs against 3 targets	Position of base $[2500, 0]m$
	Position of targets $[1000, 3400; 2800, 4600; 4500, 2000]m$
	Cruise speed vector of UAVs $[v_1, v_2, v_3] = [70, 80, 70, 90, 60]m/s$
	Turning radius vector of UAVs $[r_1, r_2, r_3] = [200, 250, 200, 300, 180]m$
	Initial heading angles of UAVs $[\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5] = [0°, 22.5°, 45°, 67.5°, 90°]$
5 UAVs against 9 targets	Position of base $[0, 0]m$
	Cruise speed vector of UAVs $[v_1, v_2, v_3] = [70, 80, 70, 90, 60]m/s$
	Turning radius vector of UAVs $[r_1, r_2, r_3] = [200, 250, 200, 300, 180]m$
	Initial heading angles of UAVs $[\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5] = [0°, 22.5°, 45°, 67.5°, 90°]$
15 UAVs against 10 targets	Position of base $[2500, 0]m$
	Randomly select the position of targets in the interest area
	Randomly select the cruise speeds of UAVs between $[50 - 100]m/s$
	Randomly select the turning radius of UAVs between $[150 - 300]m$
	Randomly select the initial heading angles of UAVs between $[0° - 90°]$

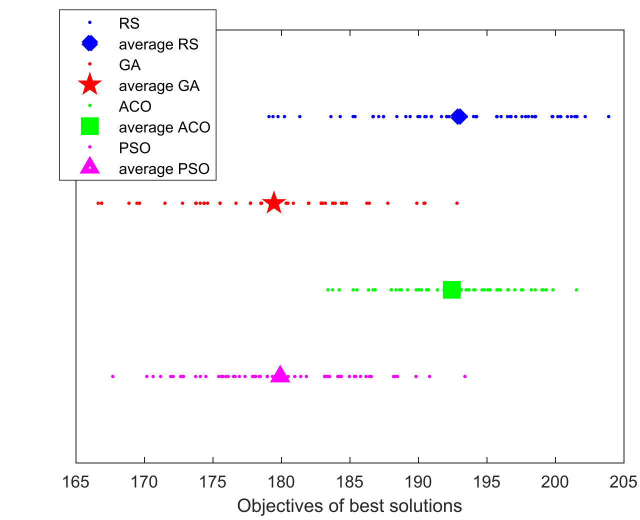
Table 4 Simulation parameters in four scenarios

Methods	Simulation parameters
RS	$N_p = 100$
GA	$N_p = 100, N_e = 4, N_{cr} = 66, N_{mu} = 30$
ACO	$N_{ant} = 100, \alpha = 1, \beta = 0.5, \rho = 0.1, Q = 1$
PSO	$N_{particle} = 100, c_1 = 0.5, c_2 = 0.7$

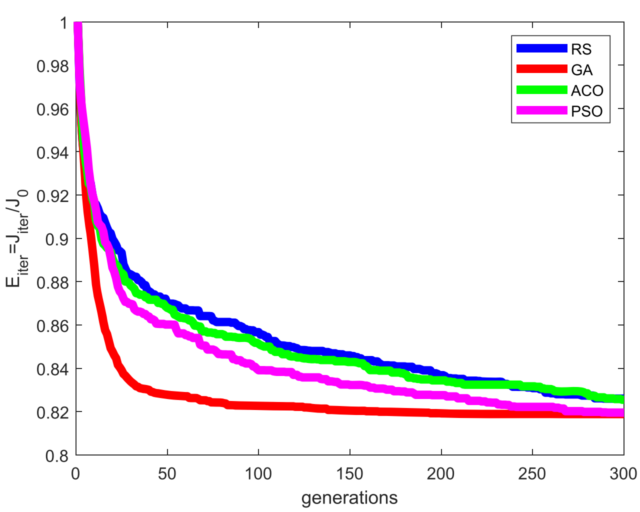
4 Simulations and Analyses

Monte Carlo simulations are used to test the optimization performance of the proposed GA for the CMTAP model. In the $5000 \times 5000m^2$ interest area, UAV team from the same base needs to perform SEAD mission on several targets, where the execution time of each task is 5s. Four SEAD scenarios in Table 3 are used to comprehensively discuss the effectiveness of the proposed GA.

RS, ACO and PSO are selected as the comparing methods. RS represents the stochastic searching algorithm, ACO and PSO represent the heuristic swarm optimization algorithms. ACO is a combinatorial optimization algorithm which simulates the ants' foraging process with pheromones [8], which has been introduced to solve the vehicle routing problem (VRP), as well as CMTAP model. PSO has simple structure equations and very few parameters to adjust, which is able to produce robust solutions within short computation time [28]. In order to prove the optimization performance of the proposed GA, the raised multi-type gene chromosome encoding strategy is extended into RS, ACO and PSO. The parameters of the proposed GA and comparing methods are shown in Table 4 (same parameters are used in four scenarios), and the number of iterations of all methods is $N_g = 300$.

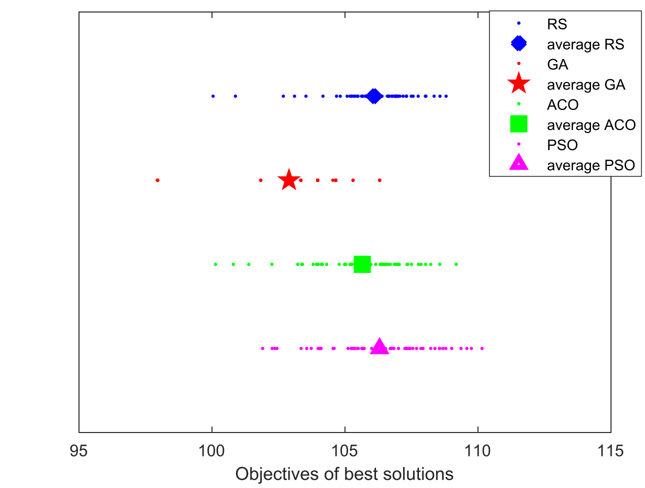


(a) Solutions

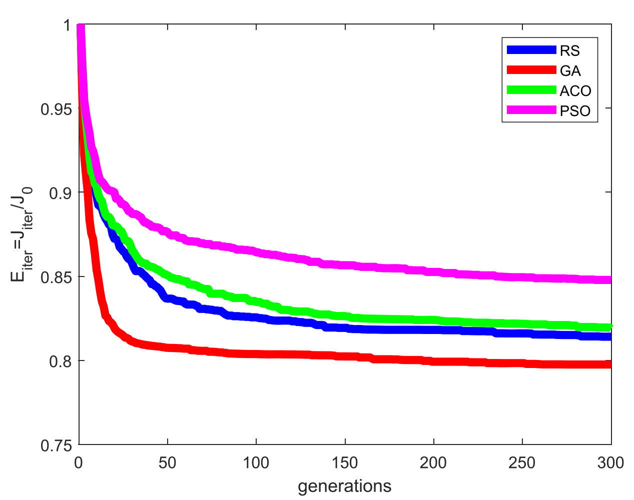


(b) Average convergence performance

Fig. 7 Monte Carlo results of four methods in scenario 1



(a) Solutions



(b) Average convergence performance

Fig. 8 Monte Carlo results of four methods in scenario 2

In Table 4, N_{ant}, α, β, ρ, Q of ACO respectively denote the number of ants, the importance index of pheromone, the influence index of pheromone heuristic information, the evaporation rate of the local pheromone trail, and the predetermined pheromone intensity. $N_{particle}$, c_1, c_2 of PSO respectively denote the number of particles, the cognitive acceleration index and social acceleration index.

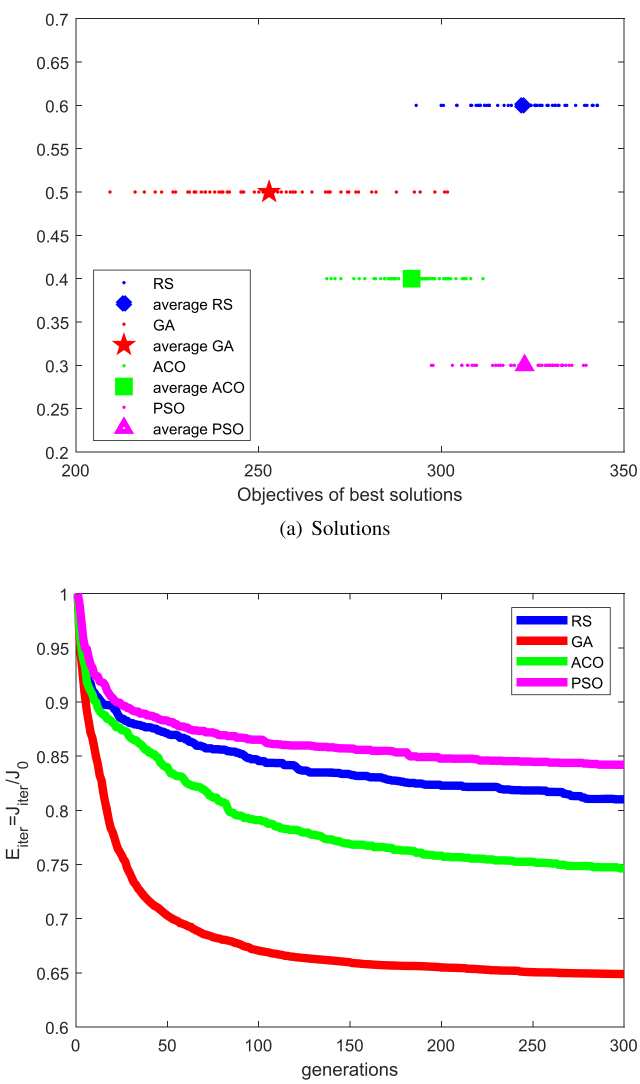
4.1 Scenario 1: 3 UAVs Against 4 Targets

In Scenario 1, the heterogeneous UAV team $\mathbf{U} = \{U_1^S, U_2^C, U_3^M\}$ needs to perform SEAD mission on four targets. Through 60 Monte Carlo runs, the results of four methods are shown in Fig. 7.

Figure 7a shows the objective values of solutions during 60 Monte Carlo runs. The smaller the objective value is, the better the solution is. Obviously, the proposed GA generate better solutions than the compared methods. Figure 7b shows the average convergence performance of four methods, where $E_{N_g} = \frac{J_{N_g}}{J_0}$ denotes the convergence value. J_0 is the initial objective value, and J_{N_g} is the objective value after N_g iteration time. The smaller E_{N_g} is, the better convergence performance the algorithm has. Figure 7b reveals that the proposed GA has better convergence speed and lower convergence value than the compared methods. To further prove the overall performance of the proposed GA, different scenarios are then discussed.

4.2 Scenario 2: 5 UAVs Against 3 Targets

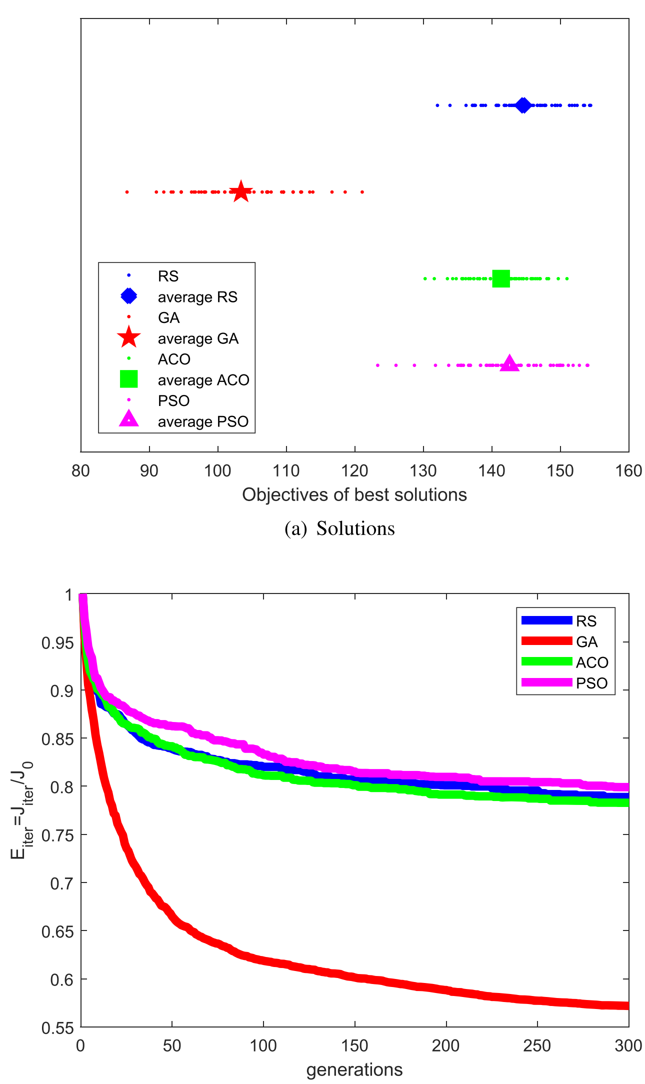
The heterogeneous UAV team $\mathbf{U} = \{U_1^S, U_2^C, U_3^C, U_4^C, U_5^M\}$ needs to perform SEAD mission on three targets. Through 60 Monte Carlo runs, the objective values of



(a) Solutions

(b) Average convergence performance

Fig. 9 Monte Carlo results of four methods in scenario 3



(a) Solutions

(b) Average convergence performance

Fig. 10 Monte Carlo results of four methods in scenario 4 solutions and average convergence performance are shown in Fig. 8.

As shown in Fig. 8a, the proposed GA is the best in both the distribution of solutions and the average value of solutions during 60 Monte Carlo runs. Besides, Fig. 8b reflects that the convergence performance of the proposed GA is slightly better than the compared methods.

4.3 Scenario 3: 5 UAVs Against 9 Targets

Then, we increase the number of targets in the CMTAP model. The heterogeneous UAV team $\mathbf{U} = \{U_1^S, U_2^C, U_3^C, U_4^C, U_5^M\}$ needs to perform SEAD mission on nine targets. Through 60 Monte Carlo runs, the objective values of solutions and average convergence performance of four methods are shown in Fig. 9.

Figure 9 demonstrates that the proposed GA has obvious advantages in the scenario of 5 UAVs against 9 targets. On the one hand, the distribution of solutions and the average values of solutions of the proposed GA are superior to that of the compared methods. On the other hand, the convergence performance of the proposed GA is significantly better than that of the compared methods.

4.4 Scenario 4: 15 UAVs Against 10 Targets

The heterogeneous UAV team $\mathbf{U} = \{U_1^S, \cdots, U_5^S, U_6^C, \cdots, U_{10}^C, U_{11}^M, \cdots, U_{15}^M\}$ is allocated to perform SEAD mission on ten targets. Through 60 Monte Carlo runs, the objective values of solutions and average convergence performance of four methods are shown in Fig. 10.

Compared with scenarios 1-3, the CMTAP model of scenario 4 is the largest. We can see from Fig. 10 that compared with other methods, the proposed GA not only obtains the best solutions, but also has outstanding convergence performance. Obviously, the proposed GA remarkably realizes the cooperative task assignment of heterogeneous UAVs against multiple targets in scenario 4.

Table 5 Monte Carlo results of four methods in different scenarios

Scenarios	UAV team	Optimization results (min,max,avg,E_{N_g})			
		GA	RS	ACO	PSO
3 UAVs against 4 targets	Homogeneous	**147.30**	161.01	159.16	163.67
		178.00	185.48	182.55	182.84
		160.95	174.25	171.80	173.88
		0.7729	0.8229	0.8037	0.8441
	Heterogeneous	**166.62**	180.62	183.39	167.69
		192.81	204.36	201.54	193.39
		179.45	195.01	192.43	179.91
		0.8129	0.8273	0.8255	0.8196
5 UAVs against 3 targets	Homogeneous	**96.04**	100.96	101.55	98.93
		106.31	111.53	108.43	109.30
		101.05	105.58	105.33	105.51
		0.8189	0.8260	0.8220	0.8489
	Heterogeneous	**97.96**	100.05	100.14	101.91
		106.31	108.81	109.19	110.16
		102.90	106.10	105.66	106.31
		0.8056	0.8295	0.8188	0.8477
5 UAVs against 9 targets	Homogeneous	**202.91**	284.93	257.82	289.62
		273.02	331.32	297.44	332.22
		239.11	312.16	283.50	313.72
		0.6419	0.8152	0.7542	0.8347
	Heterogeneous	**209.31**	293.10	268.63	297.27
		301.66	342.68	311.38	339.60
		252.86	322.16	291.86	322.77
		0.6488	0.8101	0.7463	0.8420
15 UAVs against 10 targets	Homogeneous	**107.37**	148.71	149.19	150.79
		136.50	175.66	174.45	179.19
		121.60	166.97	165.64	166.97
		0.6091	0.8111	0.8185	0.8368
	Heterogeneous	**86.74**	132.04	130.24	123.32
		121.06	154.40	150.94	153.98
		103.38	144.56	141.33	142.57
		0.5718	0.7888	0.7828	0.7991

4.5 Discussions

To comprehensively illustrate the effectiveness and robustness of the proposed GA for the CMTAP model, the detailed task assignment results of four methods in the above four scenarios are provided in Table 5. Besides, the homogeneous combat UAV team is also considered.

Table 5 presents the minimum (min), maximum (max) and average (avg) objective values of the solutions over 60 Monte Carlo runs. In addition, the average convergence indexes $E_{N_g} = \frac{J_{N_g}}{J_0}$ of four methods are exhibited in Table 5. The best results among different methods are highlighted in bold.

We can see from Table 5 that:

1) In all four scenarios, the proposed GA has lowest objective values (min/avg/max values). The superiority of the proposed GA in the min/max/avg objective values is further revealed when dealing with large-scale SEAD scenarios.
2) In scenarios 1-2, the convergence indexes E_{N_g} of four methods all reach around 0.8. In scenarios 3-4, E_{N_g} of the proposed GA reaches 0.58-0.65, while the comparing methods still remain around 0.8. With the increasing of the model size, the convergence performance of the proposed GA enhances prominently.

5 Conclusions

Cooperative multiple task assignment problem (CMTAP) is a NP-hard combinational optimization problem. In this paper, we studied the CMTAP model to allocate heterogeneous UAVs to perform classify, attack and verify tasks consecutively on multiple ground stationary targets. To address this problem, we proposed a modified genetic algorithm (GA) with multi-type-gene chromosome encoding strategy. The chromosome population built by the encoding strategy satisfies the UAV heterogeneity, task coupling and task precedence constraints. By the introduction of Dubins car model, the objective function of each chromosome is calculated, as well as its fitness value. Then, according to the designed encoding scheme, corresponding crossover operator and multiple mutation operators are presented to trade-off the global search ability of GA and the diversity of GA population. The simulation results demonstrate the effectiveness and robustness of the proposed GA for the CMTAP model.

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