Applied Soft Computing 126 (2022) 109310

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Pigeon-inspired fuzzy multi-objective task allocation of unmanned aerial vehicles for multi-target tracking

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ARTICLE INFO

Article history:
Received 29 June 2021
Received in revised form 30 June 2022
Accepted 6 July 2022
Available online 16 July 2022

Keywords:
Unmanned aerial vehicles
Task allocation
Multi-target tracking
Multi-objective optimization
Pigeon-inspired optimization

ABSTRACT

In this paper, a pigeon-inspired fuzzy multi-objective optimization algorithm is proposed for task allocation of multiple unmanned aerial vehicles tracking multiple ground targets in urban environment. Firstly, a multi-objective integer programming of task allocation, involving minimum total flight distance, best task allocation balance and minimum completion time, is established. Secondly, fuzzy two-phase optimization based on the relaxed order of desirable satisfactory degrees is proposed to formulate mixed integer programming regarding the linguistic importance preference of objectives. Then, an adaptive pigeon-inspired algorithm combined with auction mechanism is proposed to solve the optimization model. The position of pigeon is defined as the bidding price given by unmanned aerial vehicle for target. To satisfy the constraints and avoid existence of inferior pigeons, the auction mechanism is designed to decode the pigeon position into a feasible task allocation scheme. Finally, by comparing with the conventional particle swarm optimization, simulations validate the effectiveness and efficiency of the proposed method.

1. Introduction

Recent years, unmanned aerial vehicle (UAV) has attracted more attention and been widely applied in military and civil engineering. Especially, tracking ground targets by UAV becomes one of the most popular issues [1,2]. However, in many complex scenarios, it is difficult for single one UAV to complete tracking task such that exploring multiple UAVs cooperation ability is urgent. At present, there are some studies on cooperative tracking of ground targets by UAVs [3,4].

For multi-target tracking application, target detection, task allocation and path planning are the key problems. Effective detection is the basis of tracking ground targets by UAVs, however, the difficulty is to achieve good accuracy and real-time performance. Image processing is the important issue and often used in target detection, e.g. background difference [5], template matching [6], and machine learning [7]. Due to its excellent computation ability, the deep learning methods such as convolutional neural network (CNN) are widely applied to target detection [8]. For task allocation and path planning, the former is basis of the latter and can improve the overall task execution performance of UAVs system. However, multi-UAV task allocation problem is a non-deterministic polynomial hard (NP-hard) programming with multiple indices and constraints [9], which results in the difficulty to obtain the optimal allocation. Various complicated objectives and constraints make it hard to formulate powerful optimization model and design the effective algorithm. Moreover, increment of the numbers of UAVs and targets will cause exponential enlargement of solution space. Thereafter, finding the best matching result becomes more difficult.

Mostly, the research on multi-UAV task allocation is taken as some classical problems, such as vehicle routing [10,11], multiple traveling salesman [12,13], knapsack problem [14,15], and dynamic network flow optimization [16,17]. These problems can be abstracted into the integer programming (IP) model or the mixed-integer programming (MIP) model [18,19]. The above research focuses on multiple UAVs' investigation, search and attack, however, mainly considers task sequence. During multiple UAVs tracking moving targets, each target must be tracked by at least one UAV, and several UAVs are allowed to track the same target. In other words, the number of UAVs must be larger than targets. Consequently, the aforementioned allocation model cannot be directly used for the target tracking scenario.

In general, single one objective, e.g. total benefits [20], is used in task allocation, however, it might result in bad result. Accordingly, many indicators are proposed to comprehensively evaluate allocation performance such that multi-objective task allocation (MOTA) optimization model is formulated. For example, Wang et al. [21] used task execution time and UAV total consumption as two sub-objectives to build a multiple UAVs reconnaissance

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https://doi.org/10.1016/j.asoc.2022.109310
1568-4946/

task allocation model. Xu et al. [22] proposed a multi-objective cost model in task allocation of UAVs for plant protection, including field allocation, non-operation flight distance, and operation time difference. Nevertheless, how to handle multiple objectives effectively is not easy. Preference is essential information for all objectives and selection of optimal solution [23]. Most existing work transforms the multi-objective optimization (MOO) into a single-objective optimization (SOO) by weighted method, where the weights are expected to represent the importance of objectives and usually given by experience. However, when the objective functions are non-convex, the weighted method cannot guarantee the solution's optimality. Thus, dealing with multiple objectives effectively is a challenging work.

Many approaches have been widely used to solve task allocation, e.g. tabu search [24], artificial neural network [25], genetic algorithm [26,27], contract network market [28], and auction [29], etc. Therein, the contract network market and auction algorithms are commonly used in distributed systems. Although these methods can find a feasible task allocation result, they may also easily fall into local optimization. In recent years, the swarm intelligence optimization strategies have been attempted to task allocation due to its advantages such as fast computation speed and high optimization accuracy. These advantages benefit from imitation of biological evolution and foraging behavior. For instance, ant colony optimization (ACO) [30] and particle swarm optimization (PSO) [31] are classical swarm intelligence algorithms. ACO is positive feedback heuristic optimization inspired by ant foraging behavior, and feasible for task allocation optimization [32,33]. However, ACO suffers from some defects, e.g. too many parameters and long search time. PSO simulates the foraging process of birds and has the advantages of fewer parameters, a simple calculation process and easy implementation. Therefore, it has attracted more attentions [34,35]. However, PSO is prone to the loss of population diversity and the local optimization is often achieved as well.

Pigeon has a natural ability to navigate, which allows them to find their way home over a long distance. Inspired by this, Duan [36] proposed a new biologically inspired swarm intelligence algorithm, i.e. pigeon-inspired optimization (PIO). This algorithm possesses more significant biological characteristics than PSO, and fully considers the influence of Geomagnetism and landmarks on the pigeon swarm. PIO shows its excellent optimization performance [37,38] and has potential in dealing with task allocation. Nevertheless, at present PIO applications in the UAV field are mainly focused on path planning [39] and controller design [40]. There is little research on task allocation of multiple UAVs. The conflict between the continuous location update of PIO and the discrete task allocation results brings more difficulties. What is more, as the multi-UAV task allocation problem involving strict constraints, the position update of pigeon will produce abundant infeasible solutions. This may result in a significant adverse impact on optimization result. Therefore, it is a challenging work to apply PIO to the multi-UAV task allocation problem.

Aiming at task allocation of tracking ground targets by UAVs in urban environment, this paper proposes a PIO-based fuzzy MOO method. In order to achieve optimal tracking performance and good task allocation balance, multi-objective integer programming (MOIP) of task allocation with three objective functions is formulated. Nevertheless, it is tough to optimize multiple indices simultaneously. Therefore, according to the linguistic importance preference, all the objectives are fuzzified, and the linguistic preference is modeled as the relaxed order of desirable satisfactory degrees. Correspondingly, a fuzzy MOTA model is established. To realize tradeoff between optimization and linguistic preference, the model is further reconstructed into the two-stage mixed-integer programming (MIP). Then, the adaptive PIO algorithm is introduced to solve the optimization model. To handle the conflict between continuous position updating and discrete task allocation, the pigeon position is encoded into continuous bidding prices of UAVs. And an auction mechanism is designed in combination with constraints to decodes each pigeon position into a feasible task allocation scheme. Finally, the simulation is implemented to demonstrate the power of the proposed method by comparing with conventional PSO.

The main contributions of this paper are summarized as follows:

1. To comprehensively evaluate task allocation result of multiple UAVs tracking multiple ground targets in urban, three objective functions are proposed and multi-objective MIP model of task allocation is established.

2. The objective functions are fuzzified, and the linguistic preference among objectives is modeled as the relaxed order of desirable satisfactory degrees. Correspondingly, the two-phase optimization models are developed to replace the original MOO model.

3. The adaptive PIO algorithm is introduced. In order to handle the constraints and enable PIO to be applied to discrete task allocation, an auction mechanism is designed to decode the pigeon position into the feasible task allocation scheme.

The remainder of this paper is organized as follows. Section 2 introduces related work. Section 3 describes the task allocation problem. The fuzzy MOTA model is established in Section 4. Section 5 presents an adaptive PIO algorithm with an auction mechanism. Simulations are shown in Section 6. Finally, Section 7 draws conclusion.

2. Related work

2.1. MOTA

Generally, MOTA belongs to MOO problem and there are different formulations in various applications. In UAV clustering, Zhang et al. [41] constructed a MOTA model by defining allocated quantity, task execution benefit, resource cost and time cost as the objective functions. In UAV search and rescue scenario, Zhang et al. [42] proposed resource consumption, number of UAVs being used, and task execution time as performance indices of task allocation. For the tracking scenario, in order to ensure good tracking performance, the balance of allocation result should be considered. In MOO, preference is essential information and represents decision maker's intention. Thereby, how to obtain the preferred solution in terms of preference becomes a challenging problem. In preference, importance is the common requirement of decision maker, and generally the weighted method is used to model preference. However, it is difficult to directly present the accurate weights. For decision makers, the more convenient way is to use linguistic preference to describe importance. Narasimhan [43] used linguistic values such as "very important", "relatively important" and "important" to represent the relative importance. Chen and Tsai [44] used desirable satisfaction to reflect the fuzzy importance of objectives. On the basis, a two-phase interactive satisfying optimization method was developed for fuzzy MOO with linguistic preference to hunt the optimal solution [45]. It can be seen that satisfactory optimization is potential strategy for MOTA of UAVs.

2.2. Swarm intelligence optimization

As task allocation being a NP-hard problem, achieving the best possible solution is generally very time consuming, and impossible for large-scale scenarios. Therefore, applying swarm intelligence optimization method to this topic is a potential perspective.

In addition to ACO and PSO, many other swarm intelligence optimization algorithms have been attempted. Krishnanand et al. [46] proposed an artificial firefly algorithm for the simultaneous computation of multiple multimodal functions, where each firefly uses the probability mechanism to move to the neighbor with higher fluorescein. Xu et al. [47] utilized a discrete wolf swarm algorithm for the UAV task allocation problem in complex environment, which imitates the hunting behavior of wolves, such as wandering, calling and siege. By means of imitating bacteria's tumbling, skipping, swimming and clustering, Heba kurdi et al. [48] explored a bacteria-inspired heuristic to solve the task allocation problem. Through following the foraging behavior of multiple frog subgroups in the wetland, Eusuff et al. [49] developed a frog-leaping algorithm based on global collaborative search. The artificial bee colony algorithm mainly imitates the two basic behaviors of bee foraging: recruiting bees for food sources and abandoning food sources. Pulikanti et al. [50] combined greedy heuristic with local search and presented a new artificial bee colony algorithm for solving the quadratic knapsack problem. At present, PSO, ACO, bacterial colony and wolf swarm have been addressed in UAV task allocation. However, these methods still face defects in convergence and optimality.

2.3. PIO

Compared with other swarm intelligence algorithms, the PIO algorithm has better performance [51]. So far, it has produced many variants and has been attempted in many applications. To complete the low altitude target detection by UAV, Li and Duan [52] designed the hybrid model of edge potential function and simulated annealing PIO algorithm. Duan et al. [53] introduced PIO in the training process of echo state networks to obtain the parameters required for image restoration. Considering the weakness of random searching system in PIO, Zhang et al. [54] presented a modified PIO model adopting Gaussian strategy for the optimal formation reconfiguration problems of multiple orbital spacecrafts. All of the above work uses PIO to the continuous optimization problems. For the discrete task allocation problem, the key is to establish the relationship between discrete task allocation scheme and pigeon position. In order to solve the discrete multi-dimensional knapsack problem, Bolaji et al. [55] used a binary encoding strategy to represent pigeon position. For the problem that position updating randomly may produce solutions not satisfying the constraints, the penalty function method is used to eliminate the infeasible solutions. However, this strategy will lead to existence of many inferior pigeons such that premature convergence might occur. Accordingly, Bolaji et al. [56] adopted the cross mutation to improve the binary PIO algorithm and cancelled the negative impact of inferior pigeons by breeding individuals. However, only when the constraints are considered during encoding and decoding, it can be ensured that any pigeon position corresponds to a feasible task allocation result, and the possibility of inferior pigeons will be decreased.

3. Problem statement

In this paper, multiple UAVs are required to track multiple ground moving targets in urban effectively and efficiently. The best matching between UAVs and targets is crucial, however, the urban environment is complex such that infrastructure or obstacles might interfere with the UAVs' maneuver. Assumptions are presented in Appendix A.

Based on these assumptions, the constraints of task allocation are written as:

$$\sum_{i=1}^{N} s_{iq} \geq 1, \sum_{q=1}^{M} s_{iq} = 1, s_{iq} \in \{0, 1\} \tag{1}$$

where s_{iq} indicates the matching relationship between UAV i and target q. When $s_{iq} = 1$, UAV i is required to track target q. Otherwise, UAV i is not assigned to target q.

In task allocation of UAVs, various indices are proposed to improve tracking performance as follows:

(1) Minimum total tracking distance: In order to ensure fast tracking and save energy, the shortest total tracking distance of all UAVs should be addressed.

(2) Best task allocation balance: Each target will be tracked by at least one UAV. It is necessary to balance the numbers of UAVs being assigned to each target to avoid the case of excessive or too few UAVs tracking the same target.

(3) Minimum completion time: The period of UAV from takeoff to catching up with the target is defined as the completion time. Each UAV is expected to track one target successfully as soon as possible.

In the actual task allocation, the importance of the above three indices is different, and it is presented in Appendix B. The most important is that all the UAVs can fly towards the targets in the shortest path to save energy, so objective (1) is "very important". Then, in order to ensure the tracking performance, the allocation balance should be optimized. Therefore, (2) is regarded as "somewhat important". Finally, it is "important" to minimize the completion time (3) such that the UAV can catch up with the expected target as soon as possible.

4. Fuzzy MOTA

4.1. Objective functions

The objectives functions are formulated in the following:

4.1.1. Minimum total tracking distance

In the actual flight, there exist infrastructure or other obstacles between UAVs and targets. Hence, the tracking cost cannot be directly modeled as the shortest line distance between UAVs and targets. When there is no infrastructure or obstacle between UAV and target, the shortest distance obtained by the geographical coordinates of UAV and target is taken as the cost. Otherwise, the optimal path from UAV to target will be calculated as the cost. In this paper, the optimal path is obtained by the Rapidly-exploring Random Tree (RRT) algorithm. The objective function is written as follows:

$$\min \quad f_1 = \sum_{i=1}^{N} \sum_{q=1}^{M} s_{iq} c_{iq} \tag{2}$$

where c_{iq} represents the cost of UAV i tracking target q.

4.1.2. Minimum task allocation deviation

In order to balance the tracking distribution of UAVs, the following function is proposed:

$$\min \quad f_2 = \sum_{q=1}^{M} (n_q - \mu)/M \tag{3}$$

where $n_q = \sum_{i=1}^{N} s_{iq}$ is the number of UAVs tracking target q, and $\mu = \sum_{q=1}^{M} n_q/M$ is the average size of UAVs tracking each target.

4.1.3. Minimum completion time

It is expected that the maximum tracking cost of all UAVs is decreased as much as possible. Thereby, minimization of maximum cost is defined as minimum completion time, as follows:

$$\min \quad f_3 = \ max \ s_{iq} c_{iq} \tag{4}$$

4.2. MOTA model

The MOTA model of UAVs can be formulated as follows:

$$\begin{cases} \min \quad f_1 = \sum_{i=1}^{N}\sum_{q=1}^{M} s_{iq}c_{iq} \\ \min \quad f_2 = \sum_{q=1}^{M}(n_q - \mu)/M \\ \min \quad f_3 = \max \ s_{iq}c_{iq} \end{cases} \tag{5}$$
$$s.t. \sum_{i=1}^{N} s_{iq} \geq 1, \sum_{q=1}^{M} s_{iq} = 1$$
$$s_{iq} \in \{0, 1\}$$

The linguistic importance of the three objectives is described as:

a. f_1 is very important
b. f_2 is somewhat important
c. f_3 is important

Obviously, the allocation model (5) is a complex 0/1 MOIP with linguistic preference.

4.3. Fuzzy MOTA model

For MOO problem, the traditional weighted method possibly leads to the weak optimal solution or the result not being able to reflect the importance requirement. Moreover, it is hard to use the weighted method to quantify the linguistic importance. Therefore, fuzzy optimization is introduced, where all the objectives are fuzzified and linguistic preference is modeled.

If decision maker can give desirable values of three objective functions priori, then the corresponding MOO with fuzzy objectives can be expressed as follows:

$$\begin{array}{ll} \textit{find} & x \\ \textit{such that} & f_i(x) \rightarrow f_i^*, i = 1, 2, 3 \end{array} \tag{6}$$

where f_i^* is the goal value of the ith objective. "$\rightarrow$" represents three types of fuzzy relationships, that is "$\tilde{\leq}$", "$\tilde{\geq}$" and "$\tilde{=}$", denoting fuzzy minimization, fuzzy maximization and fuzzy equality.

"$\tilde{\leq}$" indicates that the objective function is approximately less than or equal to the perspective value.

"$\tilde{\geq}$" represents that the objective value is approximately greater than or equal to its goal value.

"$\tilde{=}$" represents that the objective function is approximately equal to the expected value. The value of membership function is called a satisfactory degree.

Commonly, linear membership functions are defined for fuzzy relations. Since the three objective functions f_1, f_2 and f_3 of task allocation are all minimization, the following formula is used as their membership functions:

$$\mu_{f_i}(x) = \begin{cases} 1 & f_i(x) \leq f_i^* \\ 1 - \frac{f_i(x) - f_i^*}{f_i^{\max} - f_i^*} & f_i^* \leq f_i(x) \leq f_i^{\max} \\ 0 & f_i(x) \geq f_i^{\max} \end{cases} \tag{7}$$

In practice, it is difficult for the decision maker to directly present the desirable value and limits of the objective. The payoff table is utilized to calculate them.

For linguistic preference, the concept of desirable satisfactory degree is introduced to formulate the following constraint [44]:

$$\mu_{f_i} \geq \mu_{f_i}^*, i \in \{1, 2, 3\} \tag{8}$$

where $\mu_{f_i}^*$ represents the desirable satisfactory degree of objective f_i. This inequality means that the optimal satisfactory degree should be superior to the desirable satisfactory degree.

In this paper, the desirable satisfactory degree is treated as an optimization variable. The order of desirable satisfactory degree is proposed to establish the importance level of the objectives. For example, the objective f_1 is "very important", and f_2 is "somewhat important". The crisp comparison relation is formulated as:

$$\mu_{f_2}^* \leq \mu_{f_1}^* \tag{9}$$

The above formula is too strict to find a feasible solution. Therefore the slack variable γ is introduced to relax the order of desirable satisfactory degrees. There is:

$$\mu_{f_2}^* - \mu_{f_1}^* \leq \gamma \tag{10}$$

When $\gamma \leq 0$, the basic importance requirement (linguistic terms order) is followed. Otherwise, when $\gamma > 0$, the fuzzy importance preference is violated.

Combining the relaxed order of desirable satisfactory degrees, the fuzzy MOTA model can be rewritten as follows:

$$\begin{array}{ll} \max & (\mu_{f_1}, \mu_{f_2}, \mu_{f_3}) \\ s.t. & \textit{membership functions } (7) \\ & \mu_{f_1} \geq \mu_{f_1}{}^*, \mu_{f_2} \geq \mu_{f_2}{}^*, \mu_{f_3} \geq \mu_{f_3}{}^* \\ & \mu_{f_2}{}^* - \mu_{f_1}{}^* \leq \gamma \\ & \mu_{f_3}{}^* - \mu_{f_2}{}^* \leq \gamma \\ & \sum_{i=1}^{N} s_{iq} \geq 1, \sum_{q=1}^{M} s_{iq} = 1, s_{iq} \in \{0, 1\} \end{array} \tag{11}$$

where $\mu_{f_1}, \mu_{f_2}, \mu_{f_3}, \mu_{f_1}{}^*, \mu_{f_2}{}^*, \mu_{f_3}{}^*, \gamma$ are real decision variables, and s_{iq} is 0/1 integer variable. Thereby the model (11) is MIP.

4.4. Two-phase models

In order to realize the tradeoff between objective optimization and linguistic preference, the MOTA model (11) is decomposed into two-phase formulations. The purpose of the first phase model is to optimize all objective functions by max–min criterion regardless of linguistic preference. The second phase model aims at maximizing the importance difference among objectives as much as possible on the basis of the first phase optimization.

The first phase model is preliminary optimization without preference information. In this paper, the max–min criterion is utilized for solution. There is:

$$\begin{array}{ll} \max & \lambda \\ s.t. & \mu_{f_i} \geq \lambda \\ & \mu_{f_i} \leq 1, i = 1, 2, 3 \\ & \textit{membership functions } (7) \\ & \sum_{i=1}^{N} s_{iq} \geq 1, \sum_{q=1}^{M} s_{iq} = 1, s_{iq} \in \{0, 1\} \end{array} \tag{12}$$

The optimal solution λ^* is called the maximum comprehensive satisfactory degree, which means that all the objectives, even the worst objective, are optimized regardless of preference.

Apparently, the feasible region of preliminary optimization is reduced greatly. There might not be a satisfactory solution. In order to obtain the preferred solution, it is necessary to present appropriate tolerance to maximum comprehensive satisfactory degree to expand the feasible region. The degree of relaxation depends on the satisfaction of decision maker. Consequently, the optimal solution λ^* of preliminary model is reckoned as the initial condition of further optimization, and the following equation is proposed.

$$\mu_{f_i} \geq \mu_{f_i}^* \geq \lambda^* - \Delta\delta, i = 1, 2, 3 \tag{13}$$

where $\Delta\delta$ is the slack parameter. The constraint (13) plays a key role in adjustment of the desirable satisfactory degree $\mu_{f_i}^*$.

To satisfy the linguistic importance requirement of multiple objectives, the second phase model, i.e. the linguistic preference optimization, is formulated as:

$$\begin{aligned}
&\min\ \gamma\\
&s.t.\ \ \mu_{f_i} \geq \mu_{f_i}^* \geq \lambda^* - \Delta\delta, i = 1, 2, 3\\
&\quad \mu_{f_2}{}^* - \mu_{f_1}{}^* \leq \gamma\\
&\quad \mu_{f_3}{}^* - \mu_{f_2}{}^* \leq \gamma\\
&\quad \textit{membership functions } (7)\\
&\quad \mu_{f_i} \leq 1\\
&\quad -1 \leq \gamma \leq 1\\
&\quad \sum_{i=1}^{N} s_{iq} \geq 1, \sum_{q=1}^{M} s_{iq} = 1, s_{iq} \in \{0, 1\}
\end{aligned} \tag{14}$$

In model (14), different relaxation $\Delta\delta$ will produce various solutions, reflecting different tradeoff between optimization and importance.

5. PIO design

5.1. Adaptive PIO

Since models (12) and (14) are MIP, the PIO algorithm is introduced for their solution, due to its fast convergence and strong optimization abilities.

In the solution space, the pigeon has two attributes: moving speed and position. The position of each pigeon represents a potential solution, and the pigeon nest represents the optimal solution. In other words, the homing behavior of pigeon shows the convergence process of the global optimal solution. The PIO algorithm includes two parts: the map and compass operator and the landmark operator. They are respectively used to simulate the navigation in different flight stages.

Through the map and compass operator, the optimal position is taken as the reference to lead the pigeons towards the optimal direction. The pigeon speed V and position X are updated by map and compass operator, expressed as follows [36]:

$$\begin{aligned}
V_i(n_1) &= V_i(n_1-1) * e^{-R*n_1}\\
&\quad + rand * (X_{gbest} - X_i(n_1-1))\\
X_i(n_1) &= X_i(n_1-1) + V_i(n_1)
\end{aligned} \tag{15}$$

where R is the map and compass operator, n_1 is the current iteration number, and X_{gbest} is the current global optimal position.

Commonly, the standard PIO algorithm easily traps in the local optimal solution. To balance the local and global search, the nonlinear dynamic inertia weight coefficient (i.e. adaptive weight coefficient) is introduced into the map and compass operator to improve the efficiency of solving task allocation. The adaptive weight coefficient is calculated as [57]:

$$\omega(n_1) = \begin{cases} \omega_{\min} - \frac{(\omega_{\max}-\omega_{\min})*(f(x_i(n_1))-f_{\min})}{(f_{avg}-f_{\min})}, & f(x_i(n_1)) \leq f_{avg} \\ \omega_{\max}, & f(x_i(n_1)) > f_{avg} \end{cases} \tag{16}$$

where $\omega_{\min}$ and $\omega_{\max}$ represent the minimum and maximum values of the inertia weight coefficient. $f(.)$ is the fitness function, f_{avg} is the average fitness value of all pigeons, and $f_{\min}$ is the minimum fitness value.

Consequently, the map and compass operator with adaptive weight coefficient can be expressed as:

$$\begin{aligned}
V_i(n_1) &= \omega(n_1) * V_i(n_1-1) - V_i(n_1-1) * e^{-R*n_1}\\
&\quad + rand * (X_{gbest} - X_i(n_1-1))\\
X_i(n_1) &= X_i(n_1-1) + V_i(n_1)
\end{aligned} \tag{17}$$

With the iteration of map and compass operator, the pigeon positions gradually approach the optimal position.

Suppose there are N_P pigeons looking for their way home. Through the landmark operator, pigeons modify their positions according to the positions of dominant pigeons. The initial dominant population is the whole population. At each iteration, according to the fitness values of the dominant pigeon group, the pigeons with poor quality (far from the destination) are discarded, and the size of dominant pigeon group is reduced in half. The remaining pigeons are taken as the current dominant pigeon group, and each pigeon in the original pigeon group is guided by the central position of the dominant pigeon group. The positions of pigeons are updated by the landmark operator, written as:

$$\begin{aligned}
N_p(n_2) &= \left[N_p(n_2-1)/2\right]\\
X_c(n_2) &= \sum \tfrac{x_i(n_2)*f(x_i(n_2))}{N_p(n_2)*f(x_i(n_2))}\\
X_i(n_2) &= X_i(n_2-1)\\
&\quad + rand * (X_c(n_2) - X_i(n_2-1))
\end{aligned} \tag{18}$$

where [.] is the round function, n_2 is the current iteration number of landmark operator, $X_c(n_2)$ is the center position of dominant pigeon group in the n_2th iteration and represents the landmark information during actual flight.

By means of the above two operators, the optimal solution can be found quickly.

PIO is used to solve the two-phase models. Since the first phase optimization problem is maximization, the fitness value is defined as:

$$f = \lambda \tag{19}$$

The second phase optimization problem is minimization, so the fitness value f is:

$$f = 1/\gamma \tag{20}$$

5.2. Decoding of pigeon position by auction mechanism

In the preliminary optimization model, the optimization variables are s_{iq}, μ_{f_1}, μ_{f_2}, μ_{f_3} and λ. While in the linguistic preference model, the optimization variables become s_{iq}, μ_{f_1}, μ_{f_2}, μ_{f_3}, $\mu_{f_1}{}^*$, $\mu_{f_2}{}^*$, $\mu_{f_3}{}^*$ and γ. When the tracking relationship s_{iq} between UAVs and targets is known, the other variables can be obtained indirectly. Hence, when using the adaptive PIO algorithm to optimize the two-stage models, only s_{iq} needs to be solved directly. Correspondingly, the pigeon position will correspond to the task allocation scheme of multiple UAVs. However, if the pigeon position is directly encoded into task allocation scheme, a rounding operation has to be added after position updating. In addition, if the constraints are not considered in the process of encoding and position updating, a large number of inferior pigeons will be generated, which probably results in reduction of accuracy. Therefore, this paper proposes a special definition of pigeon position and designs an auction mechanism for the constraints to decode pigeon position as a feasible task allocation scheme.

For N UAVs tracking M targets, the number of UAVs is taken as the dimension of solution space. The ith element, $i \in 1, \ldots, N$ of pigeon position X^j is defined as the bidding price x_i^j given by UAV i. Hence, the pigeon position $X^j = (x_1^j, x_2^j, \ldots, x_N^j)$ involves the bidding prices from all UAVs. The initial bidding price, i.e., the initial position of pigeon, is defined as the difference between the revenue and the distance from the nearest target to the UAV. Assuming that the revenue of UAVs tracking targets is β, and the minimum tracking distance of UAV i corresponding to all targets is written as c_i^{min}. Then the initial value of x_i^j is $\beta - c_i^{min}$. Then the initial position of pigeon is written as $X^j = (x_1^j, x_2^j, \ldots, x_N^j) = (\beta - c_1^{min}, \beta - c_2^{min}, \ldots, \beta - c_N^{min}), j = 1, 2, \ldots, N_P$.

In this paper, an auction mechanism is introduced. The principle that the UAV with a higher bidding price has a higher selection priority holds. By maximizing individual benefit during

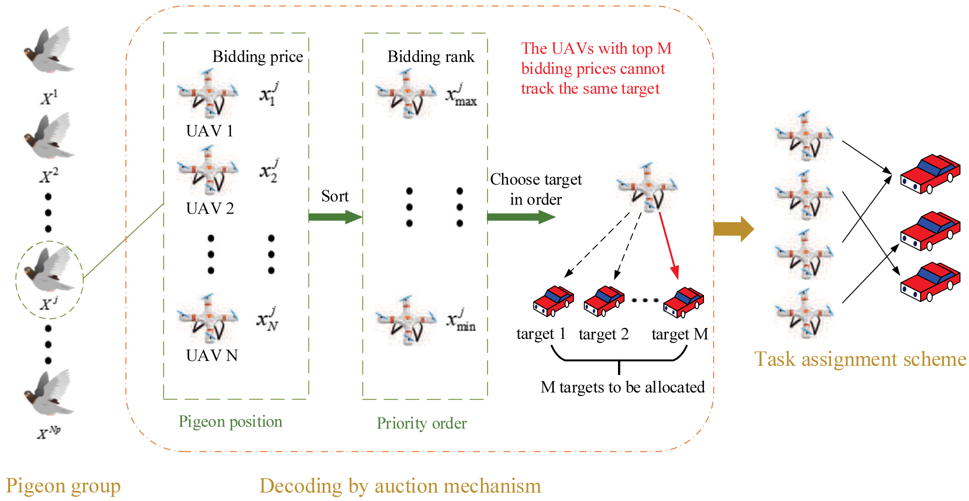

Fig. 1. Decoding of pigeon position.

bidding, the UAV selects the target with the shortest tracking distance. What is more, constraint (1) is considered to ensure that the pigeon position decoding is a feasible task allocation scheme. In order to ensure $\sum_{q=1}^{M} s_{iq} = 1$, each UAV can only select one target for tracking. To ensure $\sum_{i=1}^{N} s_{iq} \geqslant 1$, that is, all targets need to be tracked, the UAVs with the top M bidding prices cannot track the same target. The designed auction mechanism is summarized as follows:

a. The UAV with higher bidding price has higher priority. In light of the priority order, tasks of UAVs are assigned in turn.

b. The target with the shortest distance to UAV i is selected as the matching object.

c. Each UAV can only select one target. To ensure all targets being tracked, the UAVs with top M bidding prices cannot track the same target, while the other UAVs can directly choose the nearest from the rest targets as their objects.

The procedure of pigeon position decoded into task allocation scheme is shown in Fig. 1. In terms of the bidding price information given by each UAV, UAVs are is ranked from high to low, and x^j_{max} is the highest bidding price and x^j_{min} is the lowest bidding price of jth pigeon. The UAV with a higher biding price has higher priority, and then each UAV will select the tracking target in turn according to auction mechanism 'b' and 'c'. Thereafter, the pigeon position is decoded into a task allocation scheme.

To better illustrate the initial position of pigeons and decoding process, an example is given below. Table 1 shows the distance cost when 5 UAVs track 3 targets. Assume that the revenue of all UAVs is 100, the minimum tracking distances of these UAVs are 10, 20, 30, 25, 15, and the initial positions of pigeons are (90, 80, 70, 75, 85). UAV 1 has the highest bid price, so the nearest target 1 is assigned to UAV 1 and cannot be selected by other UAVs. Similarly, target 3 is assigned to UAV 5, and target 2 is assigned to UAV 2. UAV 3 and UAV 4 are taken as partners for tracking target 3 and target 1 respectively. Then decoding is completed.

The flowchart of the proposed PIO algorithm with auction decoding is summarized as Algorithm 1 and shown in Fig. 2.

After decoding the pigeon positions by auction mechanism, the three objective functions (1), (2) and (3) can be calculated by the matching relationship s_{iq}. Then individual minimum and maximum values of each objective can be figured out by applying the proposed PIO method to payoff table. Consequently, the membership functions of all three objectives can be built. The other optimization variables such as $\mu_{f_1}, \mu_{f_2}, \mu_{f_3}$ and the objective functions of the two-phase models can be calculated correspondingly by using the proposed PIO approach. In this method, the pigeon positions are updated iteratively. And the constraints in (12) and (14) are dealt with after auction decoding.

Table 1
Distance cost for 5 UAVs tracking 3 targets.

	Target 1	Target 2	Target 3
UAV 1	10	20	30
UAV 2	30	40	20
UAV 3	50	40	30
UAV 4	25	30	40
UAV 5	40	50	15

Algorithm 1 Optimization Algorithm of the proposed PIO

Input: N_p: the population size; N: the number of UAVs; M: the number of targets;
Output: optimal matching
Initialize each pigeon speed and position;
Determine the iteration number $N1$ of the map and compass operator and the iteration number $N2$ of the landmark operator;
$n_1 = 0$;
repeat
    Use the adaptive map and the compass operator (17) to update the speed and position of pigeon;
    Decode pigeon position into task allocation scheme by auction mechanism;
    Calculate the fitness value of each pegion, and get the current global optimal position;
    $n_1 = n_1 + 1$;
until $n_1 = N1$
$n_2 = 0$;
repeat
    Use the landmark operator (18) to modify the current pigeon position;
    Decode pigeon position into task allocation scheme by auction mechanism;
    Calculate the fitness value of each pigeon;
    $n_2 = n_2 + 1$;
until $n_2 = N2$

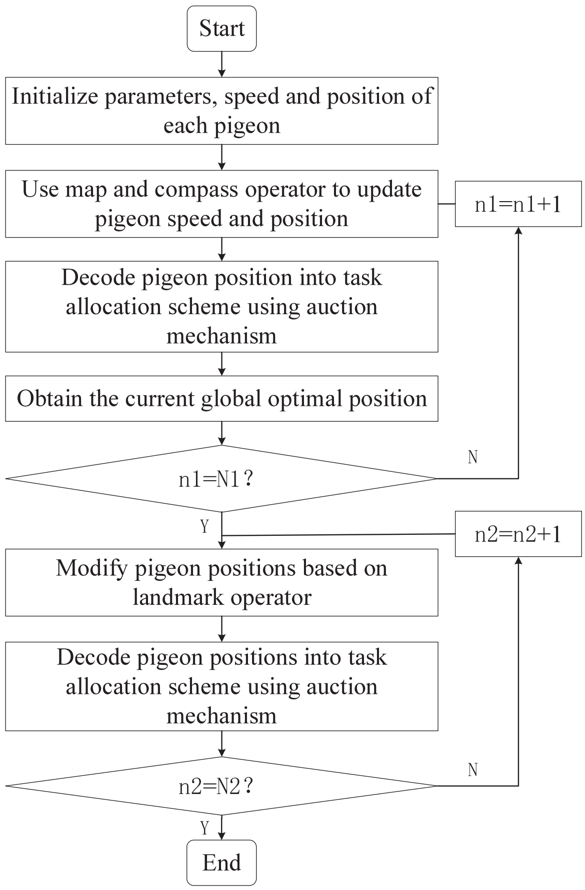

Fig. 2. Flowchart of the proposed PIO.

5.3. Computational complexity

For the map and compass operator, the evolution cost of each iteration is $o(N_pN)$. The computational complexity can be figured out using auction mechanism and evolution at each iteration, written as $o(N_pN + N_pN\log^N)$. Therefore, the complexity of the adaptive map and compass operator combining with auction mechanism is $o(N_1(N_pN + N_pN\log^N))$. While for the landmark operator, the computational complexity using auction and evolution at each iteration is $o(N_pN + N_p\log^{N_p})$. Correspondingly, the overall complexity of the landmark operator is $o(N_2(N_pN + N_pN\log^N + N_p\log^{N_p}))$. Thus, the total computational complexity of the proposed PIO is $o(N_1(N_pN + N_pN\log^N) + N_2(N_pN + N_pN\log^N + N_p\log^{N_p}))$.

5.4. Optimality test

The definition for the optimal solution of MOO problem is presented as follow.

Definition 1 (*M-Pareto Optimal Solution*). A point x^* is M-Pareto optimal solution if and only if there does not exit another solution x, such that $\mu_{f_i}(x) \geq \mu_{f_i}(x^*)$ for all i, $(i = 1, 2, 3)$ and $\mu_{f_h}(x) > \mu_{f_h}(x^*)$ for at least one h, $h \in \{1, 2, 3\}$.

Although the purpose of models (12) and (14) is to achieve the expected satisfaction, the actual optimal solution may not conform to the M-Pareto optimality. Thereby, the following test model is proposed to ensure the M-Pareto optimality.

$$
\begin{aligned}
\max\ & \varepsilon_1 + \varepsilon_2 + \varepsilon_3 \\
s.t.\ & \textit{membership functions } (7) \\
& \mu_{f_i}(x) - \varepsilon_i = \mu_{f_i}(x^*),\ i = 1, 2, 3 \\
& \varepsilon_i \geq 0 \\
& \sum_{i=1}^{N} s_{iq} \geq 1,\ \sum_{q=1}^{M} s_{iq} = 1,\ s_{iq} \in \{0, 1\}
\end{aligned}
\tag{21}
$$

where $\varepsilon_1, \varepsilon_2, \varepsilon_3$ is the error vector. Let x^* denotes the optimal solution of (12) and (14), and $\bar{x}$ denotes the optimal solution of (21). The theorem of M-Pareto optimality is given as:

Theorem. *x^* is M-Pareto optimal solution, when $\varepsilon_1, \varepsilon_2, \varepsilon_3$ are all equal to zero. Otherwise, if at least one ε_h, $h \in \{1, 2, 3\}$ is not zero, $\bar{x}$ must be the M-Pareto optimal solution.*

Proof. Assuming x^* is not M-Pareto optimal when $\varepsilon_1, \varepsilon_2, \varepsilon_3$ are all zero, $\bar{x}$ must be the M-Pareto optimal. According to the definition of M-Pareto optimal, $\mu_{f_i}(\bar{x}) \geq \mu_{f_i}(x^*)$, $(i = 1, 2, 3)$ must hold, and $\mu_{f_h}(\bar{x}) > \mu_{f_h}(x^*)$ for at least one h, $h \in \{1, 2, 3\}$. In other word, there must exist at least one non-zero ε_h, which is contrary to the fact that $\varepsilon_1, \varepsilon_2, \varepsilon_3$ are zero. So x^* is M-Pareto optimal when all ε are zero.

If at least one ε_h is not zero and $\bar{x}$ is not the M-Pareto optimal solution, there will exist another M-Pareto optimal solution $\tilde{x}$ which must be the optimal solution of (21). It is contrary to the fact that $\bar{x}$ is the optimal solution. Hence, $\bar{x}$ must be the M-Pareto optimal solution when at least one ε_h is not zero.

5.5. Algorithm steps

The steps of the proposed method are listed as follows:
Step 1: Build the MOTA model;
Step 2: Calculate the distance cost c_{iq}: when there is no obstacle between the UAV and the target, the shortest distance is selected directly; otherwise, the path length is determined using the RRT algorithm;
Step 3: Apply the adaptive PIO method with auction to the payoff table to formulate membership functions and build the fuzzy MOTA model;
Step 4: Transform the model into two-phase models;
Step 5: Solve these two models using the proposed PIO algorithm;
Step 6. Guarantee M-Pareto optimality using the test model.

6. Simulations

To validate the effectiveness and efficiency of the proposed method, a series of simulations are implemented by comparing with the conventional PSO algorithm. The three-dimension (3D) urban environment is presented in Fig. 3. Various cases are considered, involving numbers of UAVs and targets, and different initial positions.

The initial parameters of the proposed PIO algorithm are given as: population size $N_p = 20$, iteration numbers $N_1 = 40$, $N_2 = 5$, $R = 0.5$, $\omega_{\max} = 0.7$, $\omega_{\min} = 0.4$. The PSO algorithm are also applied to models (12) and (14).

6.1. 5 UAVs and 3 targets

6.1.1. Case 1

The initial position of UAVs and targets are listed in Table 2, and the matching relationship between UAVs and targets is listed in Table 3. The RRT algorithm is used for path planning of obstacles. Figs. 4 and 6 show the task allocation result and the

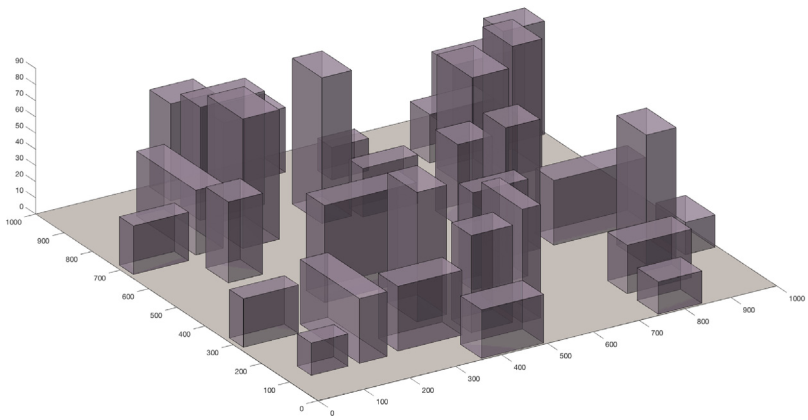

Fig. 3. Urban environmental model.

Table 2
The initial positions of UAVs and targets in Case 1.

UAV	1	2	3	4	5
X	940	708	44	656	36
Y	488	800	964	936	244
Z	3	3	3	3	3
Target	1	2	3		
X	92	580	240		
Y	516	360	816		
Z	0	0	0		

Table 3
Matching between UAVs and targets in Case 1.

PIO	UAV	1	2	3	4	5
	Target	2	2	3	1	1
PSO	UAV	1	2	3	4	5
	Target	2	2	3	3	1

tracking path in the two-dimension (2D) urban environment using our PIO and PSO, respectively (The triangle symbol represents UAV, and the dot represents target. The purple line denotes the matching relationship between UAV and corresponding target, and the orange line is the tracking path). Figs. 5 and 7 are their 3D tracking path. The satisfactory degrees of three objectives using the proposed PIO are (1, 1, 1), while they are (0.8055, 0.9985, 0.9239) using PSO, shown in Fig. 8. The satisfactory degree of each objective by PIO is bigger than that by PSO. Obviously, the performance of our PIO is better than PSO.

6.1.2. Case 2
The sizes of UAVs and targets are the same as in Case 1, but the initial position of UAVs and targets of Case 2 are different. Figs. 9 and 10 show the assignment results by our PIO and PSO. The satisfactory degrees of objectives are (1, 1, 1) and (0.2909, 1, 0.5504), as shown in Fig. 11. The proposed PIO shows better performance.

6.2. 12 UAVs and 5 targets

6.2.1. Case 3
12 UAVs and 5 targets have different original positions. Fig. 12 shows the position and matching relationship between UAVs and targets using PIO. The simulation result by PSO is shown in Fig. 13. From Fig. 14, the satisfactory degrees are (0.9057, 0.9991, 0.8071) using the proposed PIO and those are (0.6625, 0.6661, 0.6913) using PSO. It is apparent that our PIO is better than PSO.

6.2.2. Case 4
The initial locations of UAVs and targets are changed and the results are shown in Figs. 15 and 16. Fig. 17 compares the satisfactory degrees of PIO and PSO, which are (0.9103, 0.4998, 1) and (0.2488, 0.2499, 0.8303) respectively. The performance of PIO is still better than PSO in this case.

6.3. 20 UAVs and 10 targets

6.3.1. Case 5
Figs. 18 and 19 show the task allocation results by two methods. And the satisfactory degrees are (0.8333, 0.8329, 0.739) using PIO and (0.4569, 0.5831, 0.3899) using PSO (Fig. 20). The power of PIO is validated.

6.3.2. Case 6
Similarly, the UAVs and targets have different original positions in this case. The task allocation results are shown in Figs. 21 and 22. From Fig. 23, it can be seen that the satisfactory degrees of the proposed PIO are higher than PSO, which are (0.8463, 0.6996, 0.8625) and (0.7608, 0.5997, 0.2954).

From Figs. 4–26, it can be seen that the proposed PIO and PSO can both complete the task assignment of tracking multiple targets. However, Figs. 8, 11, 14, 17, 20 and 23–26 show the satisfactory degrees of these objective functions in all the cases using PIO are greater than or equal to by PSO. Apparently, all the objectives have better optimization performance by PIO. Thereby, it can be concluded that our PIO is superior to PSO in solving the formulated MIP. In addition, although it seems the order of satisfactory degrees in some cases does not conform to the linguistic importance, in reality the order of desirable satisfactory degrees meets the fuzzy importance requirement. By formulating multiple objective functions, not only tracking performance is realized, but also allocation balance is considered. In summary, the proposed PIO method has a good optimization ability to deal with multi-objective MIP.

7. Conclusion

This paper addresses the task allocation problem of tracking multiple targets using multiple UAVs in the urban environment. A pigeon-inspired fuzzy optimization method is proposed for MOTA of UAVs with linguistic preference. The model with multiple objectives, including total tracking distance, task allocation balance, and completion time, is established. For linguistic importance preference, the relaxed order of desirable satisfactory degrees is introduced, and the two-phase fuzzy models are formulated correspondingly. The enhanced PIO algorithm is designed by combining with adaptive PIO and auction mechanism to solve the

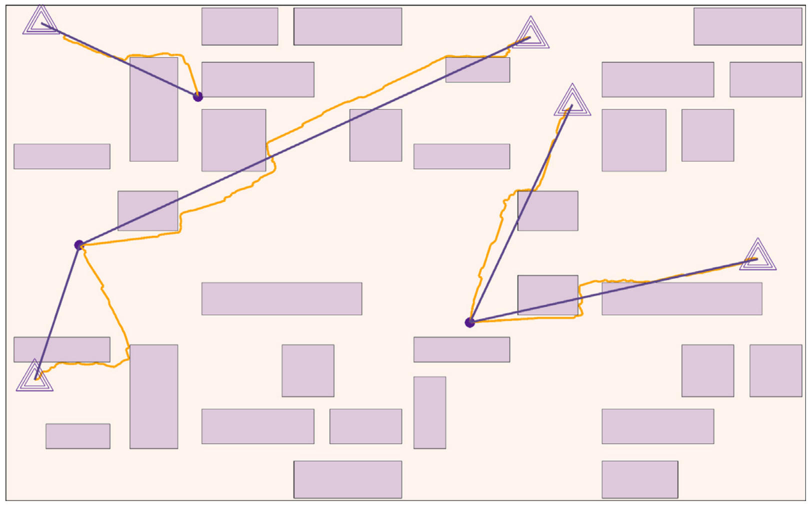

Fig. 4. 2D UAV task allocation result and tracking path using our PIO in Case 1.

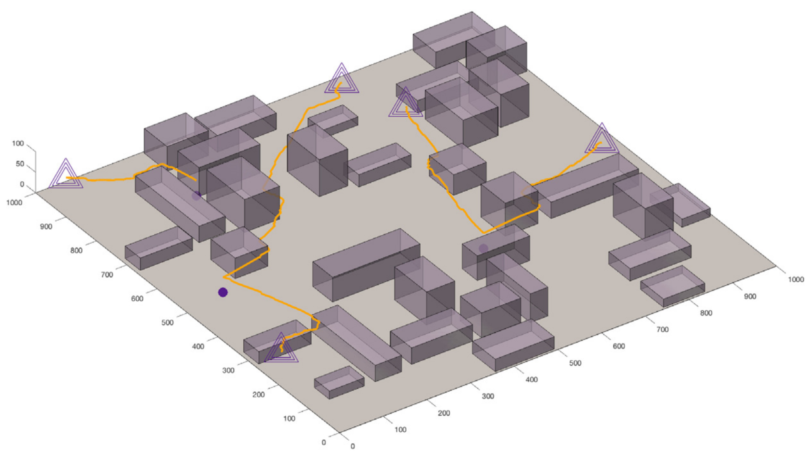

Fig. 5. 3D UAV tracking path using our PIO in Case 1.

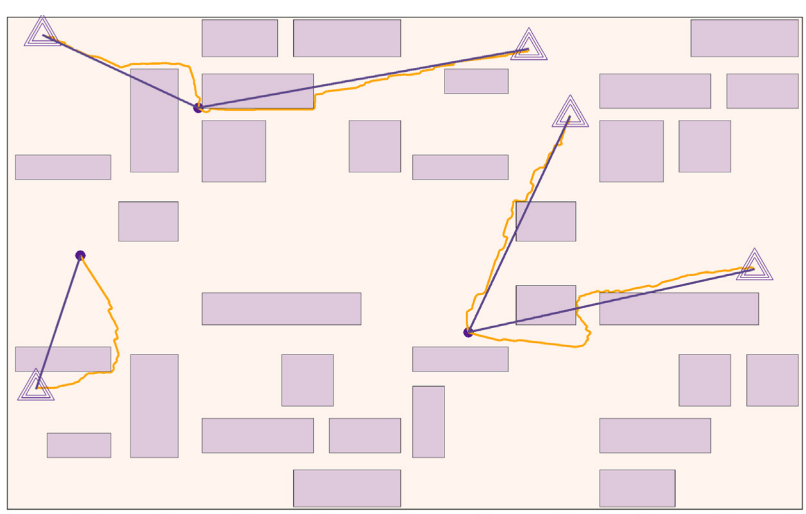

Fig. 6. 2D UAV task allocation result and tracking path using PSO in Case1.

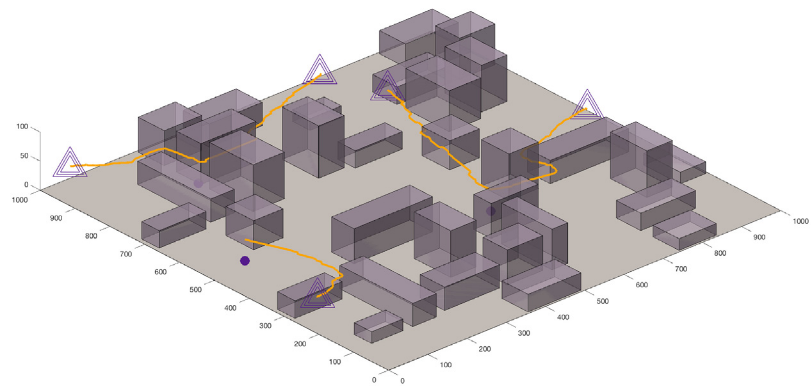

Fig. 7. 3D UAV tracking path using PSO in Case 1.

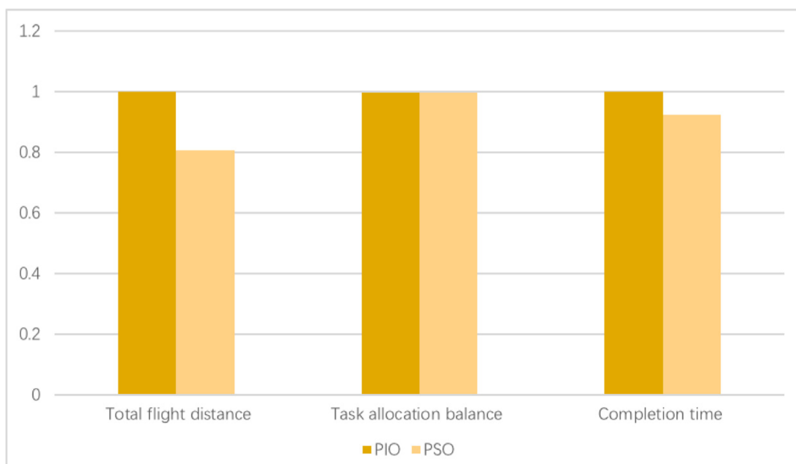

Fig. 8. Satisfactory degrees of three objective functions in Case 1.

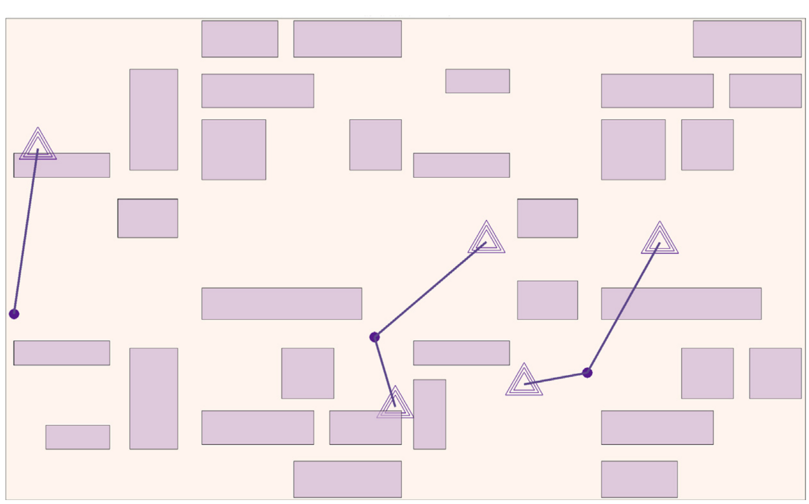

Fig. 9. 2D UAV task allocation result using our PIO in Case 2.

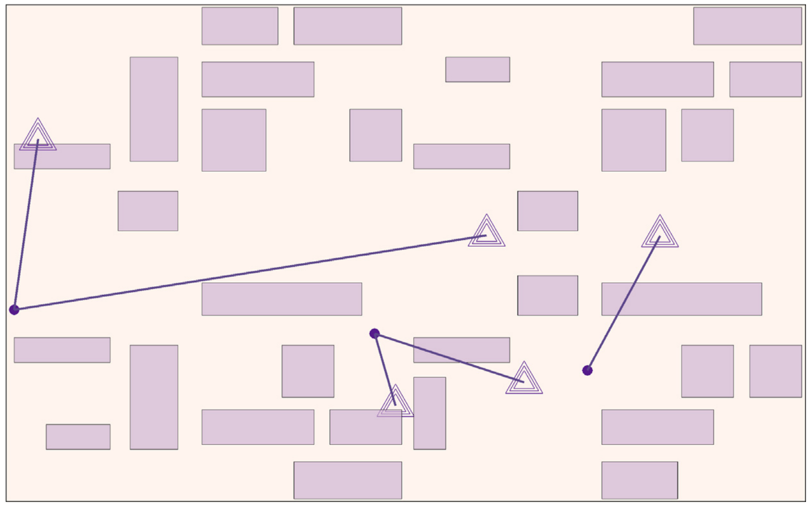

Fig. 10. 2D UAV task allocation result using PSO in Case 2.

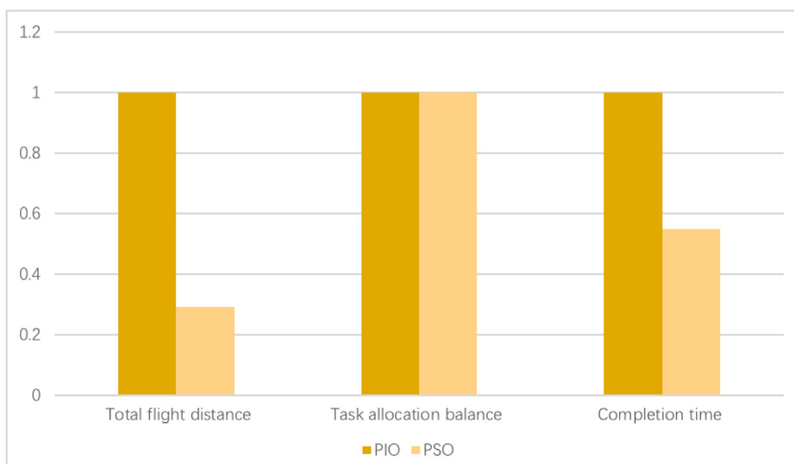

Fig. 11. Satisfactory degrees of three objective functions in Case 2.

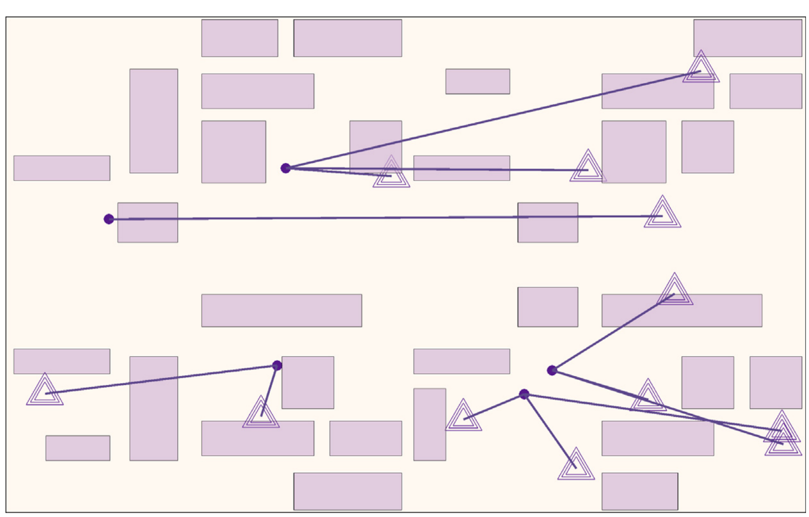

Fig. 12. 2D UAV task allocation result using our PIO in Case 3.

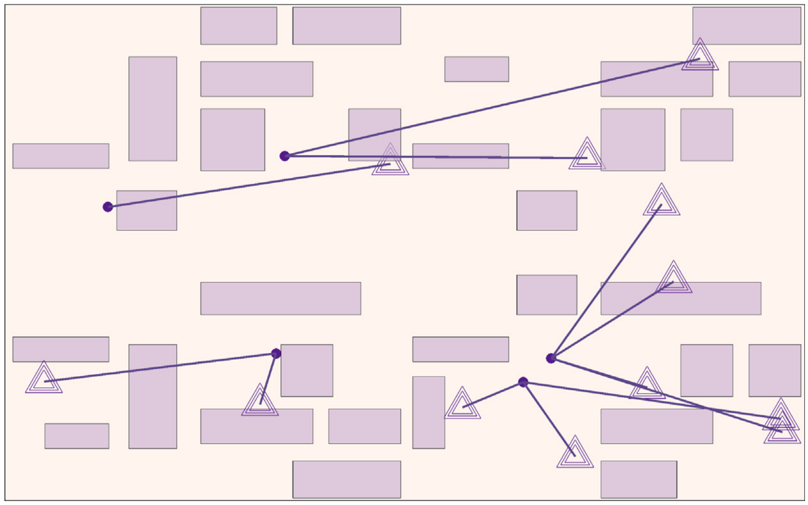

Fig. 13. 2D UAV task allocation result using PSO in Case 3.

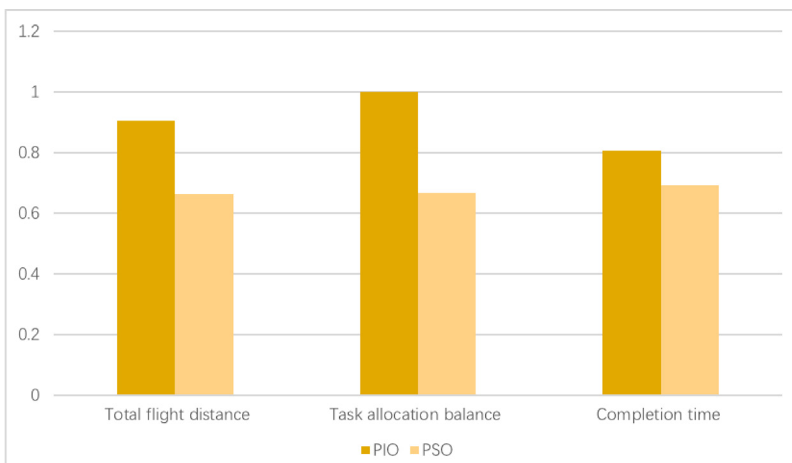

Fig. 14. Satisfactory degrees of three objective functions in Case 3.

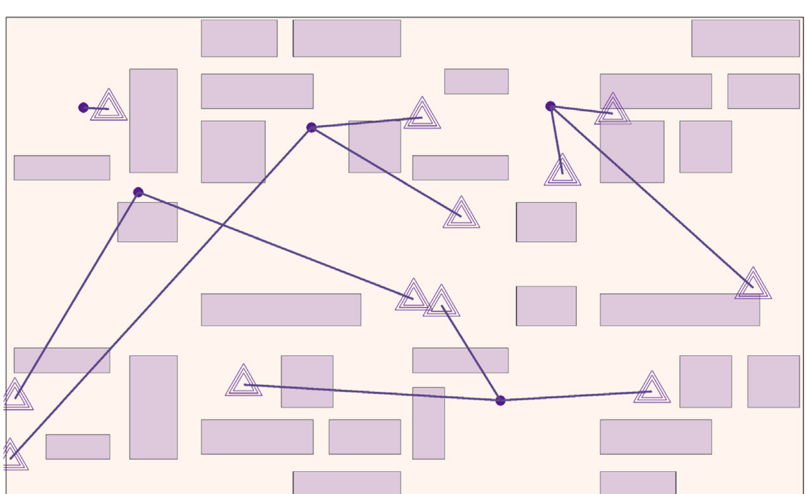

Fig. 15. 2D UAV task allocation result using our PIO in Case 4.

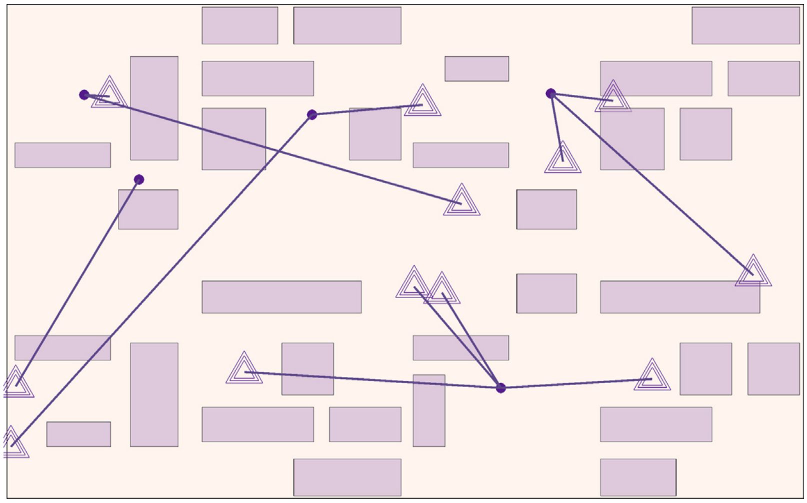

Fig. 16. 2D UAV task allocation result using PSO in Case 4.

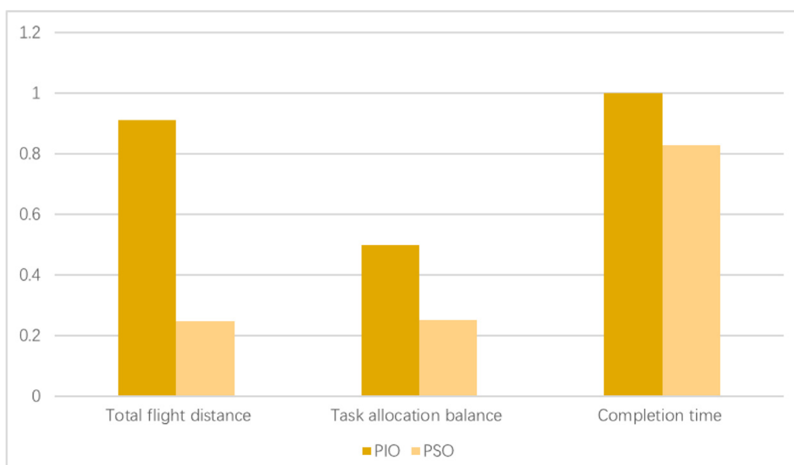

Fig. 17. Satisfactory degrees of three objective functions in Case 4.

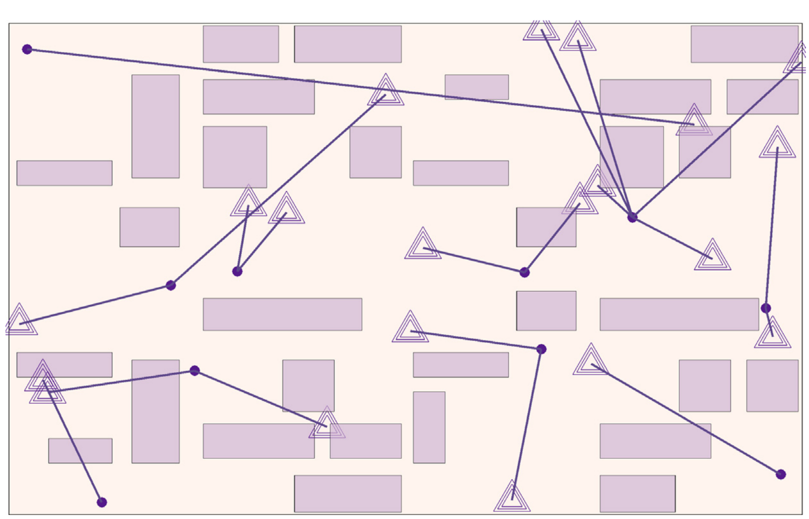

Fig. 18. 2D UAV task allocation result using our PIO in Case 5.

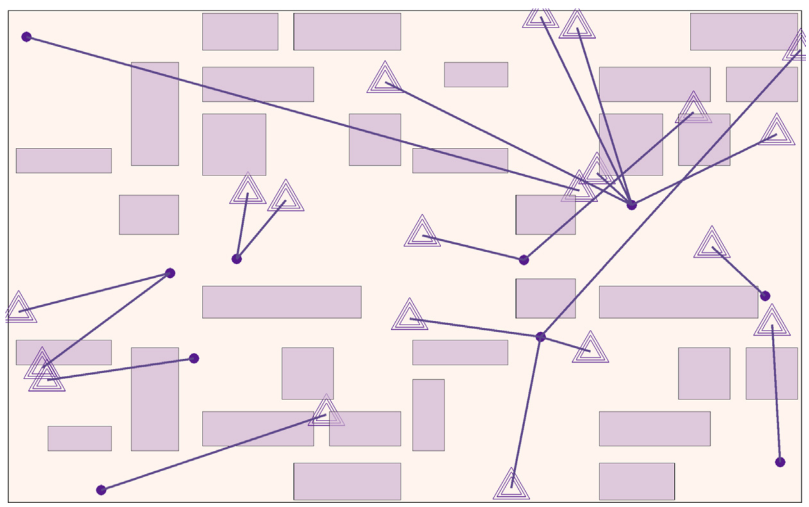

Fig. 19. 2D UAV task allocation result using PSO in Case 5.

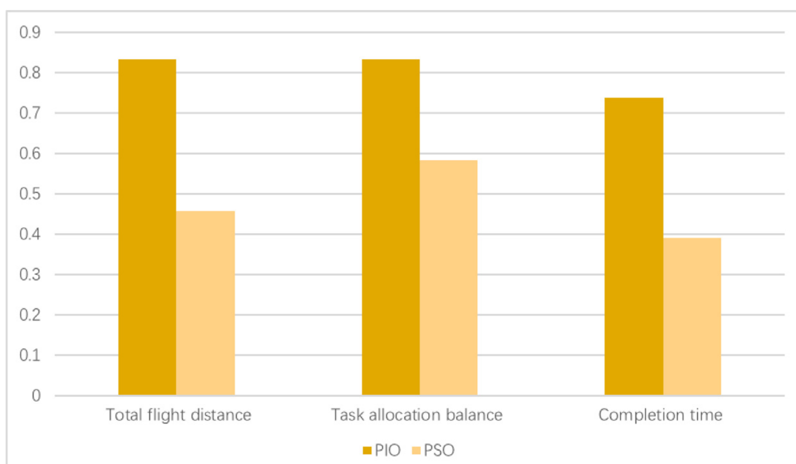

Fig. 20. Satisfactory degrees of three objective functions in Case 5.

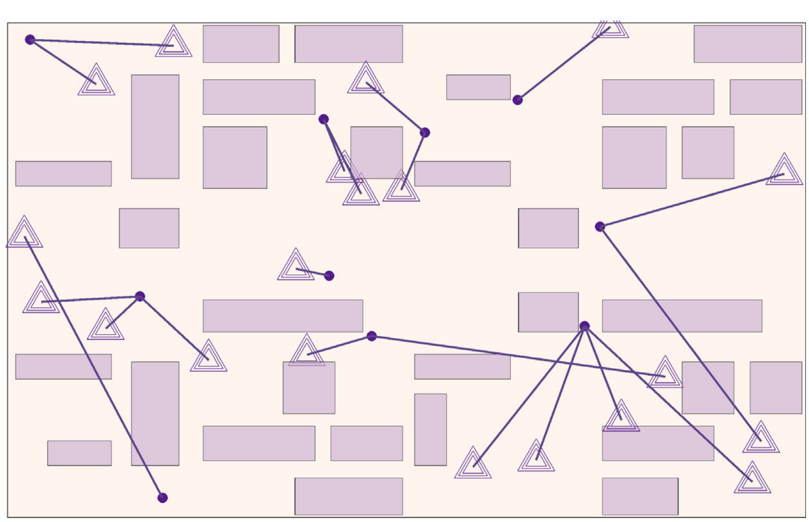

Fig. 21. 2D UAV task allocation result using our PIO in Case 6.

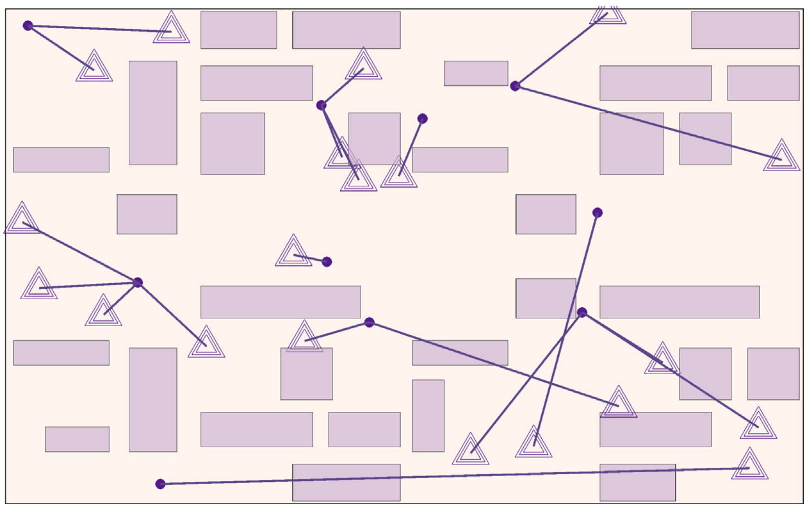

Fig. 22. 2D UAV task allocation result using PSO in Case 6.

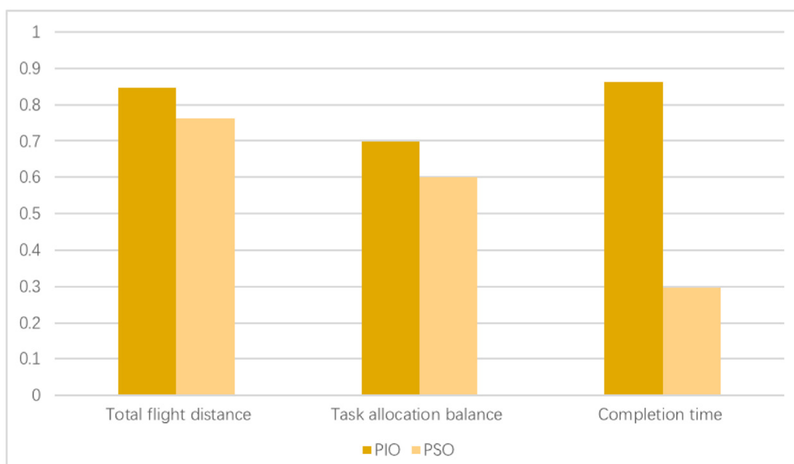

Fig. 23. Satisfactory degrees of three objective functions in Case 6.

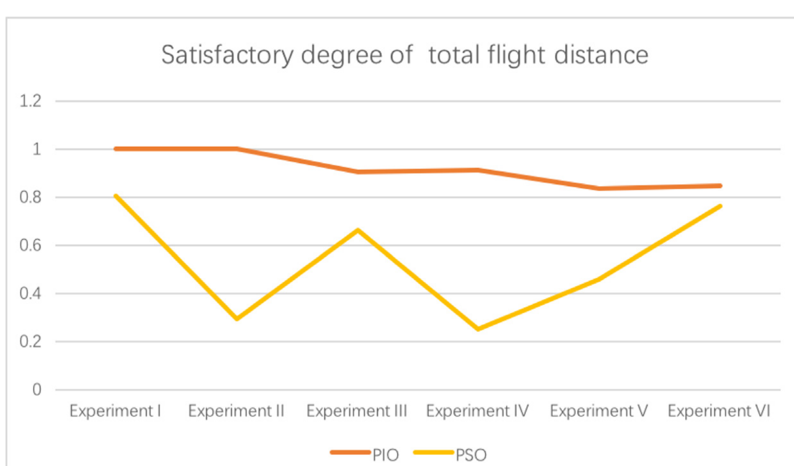

Fig. 24. Satisfactory degree of total flight distance.

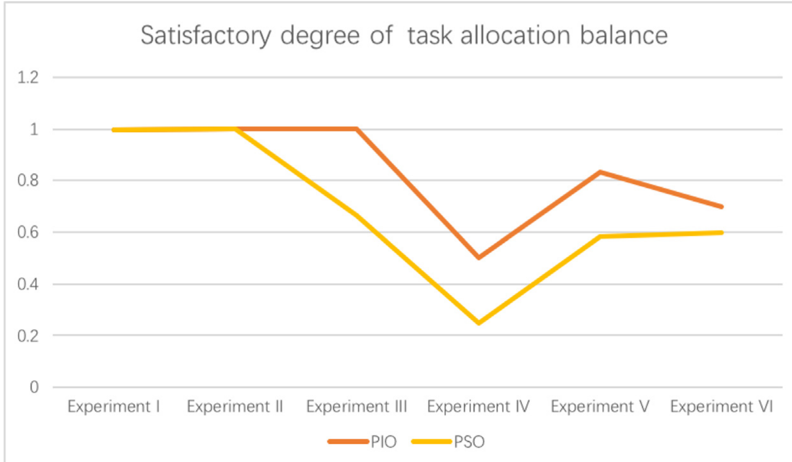

Fig. 25. Satisfactory degree of task allocation balance.

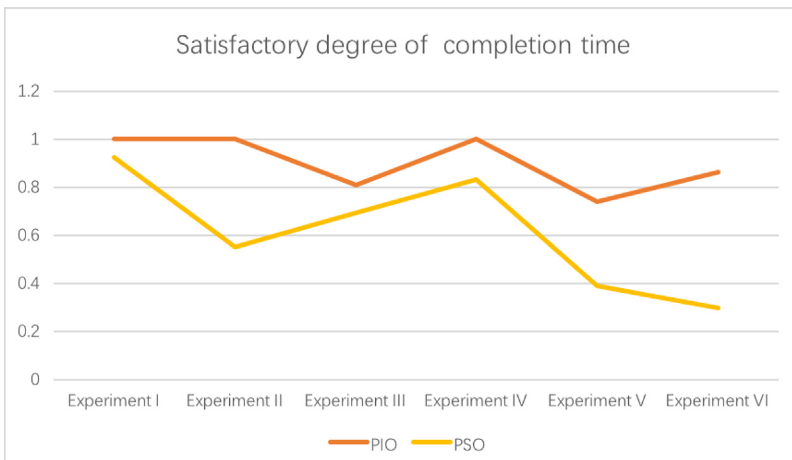

Fig. 26. Satisfactory degree of completion time.

two-phase MIP models. A series of simulations are implemented, and the effectivity and efficiency of the proposed method are validated. This paper assumes that UAVs possess all target states. In fact, target information is unknown and should be obtained by sensor measurement and the advanced computation method (e.g. CNN). That will be the future focus.

CRediT authorship contribution statement

Chaofang Hu: Conceptualization, Methodology, Supervision. **Ge Qu:** Writing – review & editing, Validation. **Yuting Zhang:** Data curation, Investigation, Writing – original draft, Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work is supported by National Natural Science Foundation of China under Grant (61773279), Aeronautical Science Foundation of China (20180748002), Science and Technology Program of Tianjin (19YFHBQY00040), and Tianjin University Innovation Foundation (2022XSU-0003). The authors are grateful to the anonymous reviewers for their helpful comments and constructive suggestions with regard to this paper.

Appendix A. Assumption of task allocation

Assumption 1. The UAVs are homogeneous and the tracking requirement for all UAVs and targets are same. That is each UAV can track arbitrary target.

Assumption 2. Each UAV can track just one target, and each target can be tracked by at least one UAV. The number of UAVs is more than that of targets.

Assumption 3. The movement of targets are known for UAVs in this paper.

Appendix B. Linguistic importance preference

The following linguistic preference terms are generally used to describe the fuzzy importance of goals.

a. "very important"
b. "somewhat important"
c. "important"
d. "general"
e. "unimportant"
f. "somewhat unimportant"
g. "very unimportant"

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