

# Multiple UAVs Mission Assignment Based on Modified Pigeon-Inspired Optimization Algorithm\*

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**Abstract**—Unmanned aerial vehicles (UAVs) have shown their superiority for applications in performing military and civilian missions. In which, multiple UAVs mission assignment is becoming more important for today's military activities. So far, there have been many bio-inspired computation algorithms for solving multiple UAVs mission assignment problems, including particle swarm optimization (PSO), differential evolution algorithm (DE) and so on. However, deficiencies of these approaches exist inevitably, which cannot satisfy the requirements of dynamic mission assignment. In this paper, a new UAV assignment model focusing on the energy consumption of UAV is brought up which can be easily applied to intelligence algorithms. Meanwhile, we propose a new approach by applying the modified Pigeon-Inspired Optimization (PIO) algorithm to solve the multiple UAVs mission assignment problem. The simulation results show that the modified PIO algorithm is more effective when compared with other state-of-the-art algorithms in addressing mission assignment problem for multiple UAVs.

## I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have exhibited a lot of incomparable advantages in carrying out many military activities, including the remarkable maneuverability and the ability to avoid the errors caused by pilots. Using multiple UAVs cooperatively to accomplish a complicated task is a very challenging problem. In which, the mission assignment for multiple UAVs is key issue which attracts many attentions and it has different objective functions according to concrete applications.

Usually, multiple UAVs mission assignment can be formulated to be an optimization problem of the air-to-ground operations to maximize the effectiveness of UAV allocation. As a NP-complete problem, some UAV mission patterns have been proposed to model it, like real-time task assignment which focuses on coalition forming of UAVs [2], Search, Identify, Engage and Assess (SIEA) missions [3], off-line UAV routing [6] and multi-mission model with constraints [9]. These models mainly deal with the time-optimization problem; L. Lin et al. brought up the time window [2], and F. Pan et al. proposed the cumulative time matrix [9]. However, the time-optimization model is incapable to describe the efficiency of allocation from the view point of UAV energy conserving. In this paper, we bring up a model concerning the energy consumption of UAVs. By introducing the cumulative property of fractional derivative into the construction of evaluation function, this model can describe the energy consumption in the mission for each UAV, which is available to any certain type of tasks.

There have been a lot of stochastic optimization algorithms being capable of dealing with multiple UAVs mission assignment,

\* This work was supported by Aeronautical Science Foundation of China under grant No. 20135851042 and No. 20125568003.

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like particle swarm optimization (PSO) [2] [4] [7] [9], differential evolution algorithm (DE) [11] [12], ant colony optimization (ACO) [5] and gravitational search algorithm (GSA) [10]. However, the aforementioned algorithms can easily fall into premature convergence and stagnate into local optimum. Therefore, the convergence rate is hardly satisfactory.

Inspired by the behavior of a swarm of pigeons, Pigeon-inspired Optimization algorithm (PIO) is proposed recently by Professor Haibin Duan of BUAA in 2014, which is a brand new swarm intelligence algorithm. Pigeons have nice senses of orientation, which contributes to their superior ability to find the most efficient way to the destination. The main tools they use to find their way home are map, compass and landmarks. Pigeons can sense the earth magnetic field and they take the sun position as a compass to form a map in their memories which guides them to the right direction. Meantime, pigeons also have the ability to recognize the landmarks they have met before so that they can obtain the best path to their destination. PIO algorithm completely reproduces these processes. The procedure of PIO can be divided into two parts: map and compass section and landmark section. In map and compass section, pigeons update their positions and velocities according to the global best position in each process of iteration. While in landmark section, pigeons update their positions using the best center position of each iteration. Through these two parts of updates, pigeons will soon find the global best position of the history.

Although the superiority of PIO algorithm outperforms other intelligent optimization algorithms, like PSO and DE, it still suffers from the common problem of premature convergence. In this paper, we introduce the conception of conditional crossover into PIO algorithm to ameliorate the search mechanism. The evolution calculation technique has been applied in PSO algorithm widely [16][17], which breed the concept of subpopulation and the hybrid techniques into swarm intelligent algorithms. Following these previous studies, we bring up a two-steps amelioration which integrates the modified map and compass factor and the improved global searching process to optimize the global search mechanism. The first step controls the balance between convergence velocity and global search ability; by modifying the dynamic process of the variation for map and compass factor to find the balance point. The second step is constructed based on the conditional crossover operation to optimize the global optima. Multiple UAVs mission assignment problem is employed to examine the effectiveness of this method, and the experiment results show the superior performance of our modified PIO algorithm.

This paper is organized as follows. We simulate one of the mission assignment scenario and build up its corresponding mathematic model with evaluation function  $f(d, a, v)$  in Section II. In Section III, the mathematical procedure of PIO algorithm is presented. Then, the modified PIO procedure is applied based on this model to optimize the evaluation function in order to find the best assignment solution, which is shown in Section IV. And Section V presents the simulation results and the comparative patterns of the modified PIO, PIO, PSO and DE are presented so as

to demonstrate the superiority of the modified PIO procedure. The conclusion is drawn in the last section.

## II. PROBLEM FORMULATION

### A. Scenario description

The specific scenario is described as follows.  $S = [0, L_1] \times [0, L_2]$  can be seen as the scale of the place where we assume all the UAVs performing their tasks. There exist  $M$  targets, denoted as  $T = \{T_1, T_2, T_3, \dots, T_M\}$  and  $N$  UAVs, denoted as  $I = \{I_1, I_2, I_3, \dots, I_N\}$ . To make our solution have more practical and strategic significance, in this case, we assume in this situation that the number of our UAVs is less than the number of targets, which indicates  $N < M$ . In order to avoid the request confliction between adjacent UAVs, each UAV is located in a certain position in advance and forms a formation with others. Here presents the necessary assumptions for our model:

- All the UAVs are homogeneous, which means all UAVs have the ability to perform the task on all targets and the differences of internal operational ability of UAVs can be ignored.
- A UAV can be allocated to execute another task after it accomplished the current one.
- In this case, all the targets have the same priority. The sequence for task execution will be ignored, and we will consider this situation in future works.

### B. Evaluation function

This section presents a new formulation using weighted aggregation approach as the criterion for the rationality of assignment. Focusing on the least energy consumption, an evaluation function  $f(d, a, v)$  is proposed according to the properties of UAVs and targets. We mainly consider the principle elements in order to simplify the space dimensions. The establishment of evaluation function is given as follows:

#### 1) Distance-evaluation function $f_d$

The ammunition or other equipment of each UAV can only be effective in a certain range. We use this range as the evaluation criterion for the weapon performance of each UAV. This can be related into the distance evaluation presented as follows:

$$f_d = \begin{cases} 1 - \frac{D}{range}, & D \leq range \\ 0, & D > range \end{cases} \quad (1)$$

where  $D$  is the Euclidean distance between  $I_i$  and  $T_i$ , and range denotes the properties of weapons of  $I_i$ . Distance function  $f_d$  describes the performance of UAV with the changing distance from targets. Its value declines as the distance increases, which means the decrease of the prosecuting possibility for  $T_i$ . Once the distance is beyond the capture range of the UAV, there is no advantage so far for  $I_i$  to destroy  $T_i$ , and we set  $f_d=0$ .

#### 2) Energy-consumption function $f_c$

When the moving distance of UAV is  $\Delta D \rightarrow 0$ , the energy consumption can be seen as a constant  $C$ . We define  $f_c$  as the energy consumption function for UAV  $I_i$ , which denotes the least energy costs for  $I_i$  prosecuting  $T_i$ . According to the memory property of fractional derivative [8], it has

$$\frac{d^q C}{dx^q} = \frac{1}{\tau(1-q)} \frac{d}{dx} \int_0^x (x-t)^{-q} C dt = C \frac{x^{-q}}{\tau(1-q)} \quad (2)$$

where  $q$  is the fractional order,  $q \in [0, 1)$ ,  $C$  is the energy consumption constant, which can be obtained by the following synthetic effectiveness of UAV, when  $q = \frac{1}{2}$ ,

$$\frac{d^q C}{dx^q} = \frac{C}{\sqrt{\pi x}} \quad (3)$$

In this case,  $x$  denotes the distance  $D$  mentioned above. And the energy consumption function  $f_c$  can be described as:

$$f_c = \frac{C}{\sqrt{\pi D}} \quad (4)$$

This function denotes the accumulation of energy consumption. It shows that the value of  $f_c$  decreases as  $D$  increases.

#### 3) Angle-evaluation function $f_a$

The direction shifts of  $I_i$  and  $T_i$  will decide if the next move is appropriate or not, which can be evaluated here by angle-evaluation function:

$$f_a = e^{-\frac{|\theta|}{\pi}} \quad (5)$$

where  $\theta$  is the relative angle between  $I_i$  and  $T_i$ , and  $\theta \in (-\frac{\pi}{2}, \frac{\pi}{2}]$ .

When target  $T_i$  is coming close to our UAV  $I_i$ ,  $\theta$  will be negative. On the other hand, when  $T_i$  is getting far away from  $I_i$ , we set  $\theta > 0$ .

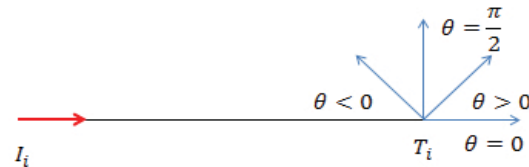


Figure 1. The definition of  $\theta$

The angle-evaluation function  $f_a$  evaluates the effect of relative angle to the assignment. As the angle increases, the probability of prosecuting  $T_i$  for  $I_i$  will decline and the situation is the same for  $f_a$ .

#### 4) Velocity-function $f_v$

Finally, we build a velocity function to describe the UAV velocity performance to assignment[13].

The velocity-function can be expressed as follows:

$$f_v = \begin{cases} e^{-|V_i - V_T|}, & |V_i - V_T| \leq 1 \text{ km/s} \\ 0, & |V_i - V_T| > 1 \text{ km/s} \end{cases} \quad (6)$$

where  $V_i$  denotes the velocity of our UAV  $I_i$ ,  $V_T$  denotes the velocity of the target  $T_i$ .

When the velocity differences between two sides are getting closer, the chance of  $I_i$  to accomplish the mission will get higher, and the value of velocity function  $f_v$  will augment.

According to these four functions, we build a comprehensive function:

$$f(d, a, v) = k_d f_d + k_a f_a + k_v f_v + k_c f_c \quad (7)$$

where  $f(d, a, v)$  is the evaluation function;  $k_d, k_c, k_a$  and  $k_v$  are the weights of distance function, energy consumption function, angle function and velocity function, respectively. Where

$$k_d + k_a + k_v + k_c = 1 \quad (8)$$

The values taken for these parameters depend on the real situation and experiments.

### III. PIO ALGORITHM

#### A. Principles of PIO algorithm

The pigeon-inspired optimization (PIO) algorithm, which proposed by Professor Haibin Duan of BUAA recently, is a new swarm intelligence algorithm using bioinformatics inspired by pigeons' behaviors. By sensing the Earth's magnetic field and following the landmarks which they are familiar with, pigeons can always find their way to the destinations as soon as possible. The procedure of PIO algorithm can be divided into two main sections:

##### 1) Map and compass section

The major principle for pigeons to find their way to the destinations is sensing the earth's magnetic field to shape the map in their brains. Meanwhile, they can adjust their direction by the compass based on the altitude of sun. In a  $D$ -dimension searching space, each pigeon  $P_i$  has two properties: position  $X_i$  and velocity  $V_i$ . Pigeons will update their positions and velocities using map and compass. The update equations in  $n$ th iteration can be given as follows:

$$V_i(n) = V_i(n-1)e^{-Rn} + rand(X_g(n) - X_i(n-1)) \quad (9)$$

$$X_i(n) = V_i(n) + X_i(n-1) \quad (10)$$

where  $X_g$  is the global best position which can be obtained from the optimum position of the whole search space,  $R$  is map and compass factor which is determined by experience and real situation, and  $rand$  is a random number, where  $rand \in [0, 1]$ .

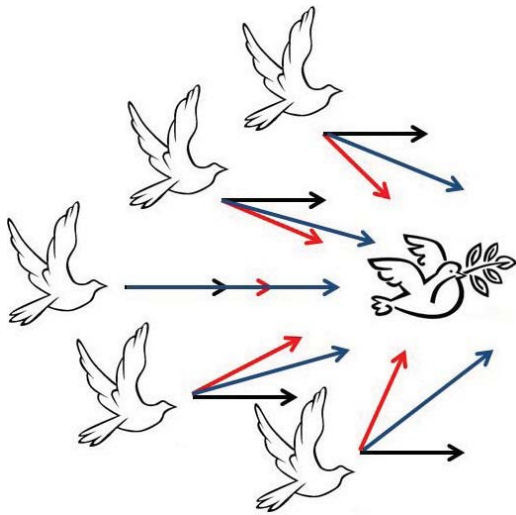


Figure 2 Map and compass section illustration

As shown in Figure2, the right-centered pigeon (global best position), pointed by red arrows from other pigeon, can be seen as a compass which can lead the other pigeons directly to better orientations. Meanwhile, each pigeon has its own map-direction (the black arrow) which is related to  $V_i(n-1)e^{-Rn}$ , and the final direction for every single pigeon is the vector sum of map-direction

and compass-direction and the resultant is denoted by the blue arrow.

##### 2) Landmark section

When getting closer to the destination, pigeons will regard the landmarks as tools to optimize their positions. Pigeons which are familiar with the landmarks will fly straightly to the destination, while the others unfamiliar with landmarks will follow them. Suppose each pigeon can fly straightly to the destination, half of the pigeons that are familiar with landmarks can find a center in the vicinity area, which can direct them to the destination as fast as possible. The number of pigeons  $N_p$  will decrease by half in each iteration process. The updating equations are given as follows:

$$N_p(n) = \frac{N_p(n-1)}{2} \quad (11)$$

$$X_c(n) = \frac{\sum X_i(n) fitness(X_i(n))}{N_p \sum fitness(X_i(n))} \quad (12)$$

$$X_i(n) = X_i(n-1) + rand(X_c(n) - X_i(n-1)) \quad (13)$$

where  $X_c$  denotes the average center of the pigeons in each iteration, and  $fitness(X_i(n))$  is the property of pigeon. For the maximizing optimization problem, we have:

$$fitness(X_i(n)) = f_{max}(X_i(n)) \quad (14)$$

and for minimizing optimization problem, we have:

$$fitness(X_i(n)) = \frac{1}{f_{min}(X_i(n)) + \epsilon} \quad (15)$$

Finally, we can get a global best position after  $n$  iterations:

$$X_p = \max(X_g(1), X_g(2), \dots, X_g(n)) \quad (16)$$

where  $X_p$  denotes the global best position of the history.

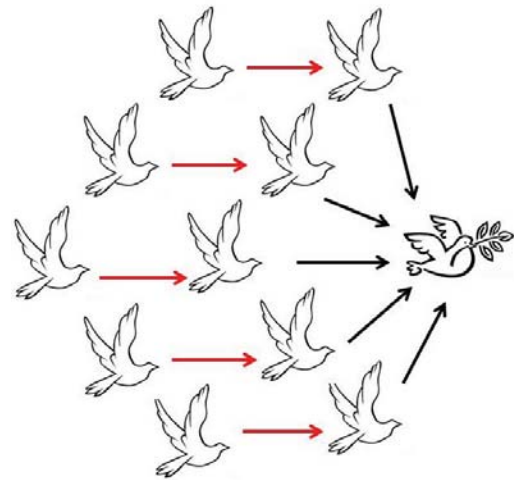


Figure 3 Landmark section illustration

As shown in Figure3, the right-centered pigeon denotes the destination in each iterative process. Pigeons close to the destination can fly straightly to it, which are shown in black arrows. While the rest half pigeons that are far from the destination will follow the pigeons close to the destination, which are presented by the red arrow. This dynamic process provides the balance between global and local search ability.

The detailed procedure of PIO algorithm is given as follows:

**Step1:** Initialize the parameters, including  $N_p, R, D, Nc1, Nc2, X_i(1), V_i(1)$ , where  $Nc1$  and  $Nc2$  denote the maximum iterations of map and compass section and landmark section respectively,  $Nc2 > Nc1$ .

**Step2:** Update  $V_i$  and  $X_i$  according to Equation (9) and (10).

**Step 3:** Update and reserve  $X_g$  using the global best position and evaluate  $X_i$ .

**Step4:** If  $n > Nc1$ , go straightly to Step5. Otherwise,  $n = n + 1$  and go back to Step2.

**Step5:** Update  $N_p, X_c$  and  $X_i$  according to equation (11), (12) and (13).

**Step6:** Update and reserve  $X_g$  and evaluate  $X_i$ .

**Step7:** if  $n > Nc2$ , go to Step8; otherwise,  $n = n + 1$  and turn back to Step5.

**Step8:** Obtain  $X_p$  according to equation (16) and reserve it as the final output.

#### IV. THE MODIFIED PIO ALGORITHM

##### A. Description of modified PIO algorithm

From the point of dynamic convergence process, the convergence velocity of PIO algorithm is famously rapid; and the optimum solution is stationary with satisfactory robustness in search process. However, a unduly fast search velocity will abate the ergodic ability of PIO algorithm in the whole search space, which can lead to the premature convergence problem. Therefore, we focus on a novel approach to enhance the global search ability, and correspondingly, address the aforementioned problem. A modified PIO algorithm is carried out which is mainly based on two procedures: the modification of map and compass factor and the improvement of the search process of global best position.

###### 1) Modified map and compass factor

The map and compass factor  $R$  is the balance controller of the search velocity and the global search ability in map and compass section. Experiment results show that the smaller  $R$  is valid to improve the global search ability, while the search velocity will get decreased with  $R$  declining. A linear-decreasing mutation strategy is put forward in [14] to cope with the dynamic inertia weight, which can be modified to accommodate our situation:

$$R = \left( R_{min} + R_{max} \times \frac{n}{Nc1} \right) \times (1 + P_R \times (rand - 1)) \quad (17)$$

where  $R_{min}$  and  $R_{max}$  are the minimum and the maximum of  $R$  respectively and  $P_R$  is the mutation probability [14].

However, linear mutation strategy is hardly consistent with the nonlinear and complex searching process of PIO algorithm. We propose a nonlinear-increasing mutation strategy here to modify this method. Given the dynamic mechanism of PIO algorithm, a time increasing scheme, i.e. the slope of  $R$  with small initial value increases with  $n$  growing, is brought up here, which greatly contributes to the regulation of global search process.

Fractional calculus is a powerful tool to help finding the proper nonlinear variation rule of  $R$ . We use the most widely applied semi-integrals to obtain the nonlinear part of equation (17) and the experiments present the best scheme as shown in equation (18):

$$R = \left( R_{min} + R_{max} \times \frac{4n^{\frac{3}{2}}}{3Nc1\sqrt{\pi}} \right) \times (1 + P_R \times (rand - 1)) \quad (18)$$

###### 2) The improved strategy on global optima searching

A subpopulation of superior pigeons is generated as the prospective objective for the global search process. Referring to the principle of genetic algorithm, a crossover is proposed here to generate refined pigeons in the iterative process. The crossover operation is stipulated in a randomly selected hybrid pool of pigeons [15]. To avoid the blindness of the hybrid procedure, crossover is confined to a certain condition, which promises the inheritance of superior individuals. For any two of the pigeons in hybrid pool,  $X_i$  and  $X_j$  in the  $n$ -th iteration:

$$\text{If } fitness(X_i(n)) < fitness(X_j(n))$$

$$X_i(n+1) = P_C X_i(n) + (1 - P_C) X_j(n)$$

$$X_j(n+1) = X_i(n+1)$$

End

where  $fitness(X_i(n))$  denotes the property of pigeon  $X_i(n)$ , and  $P_C$  is the crossover probability.

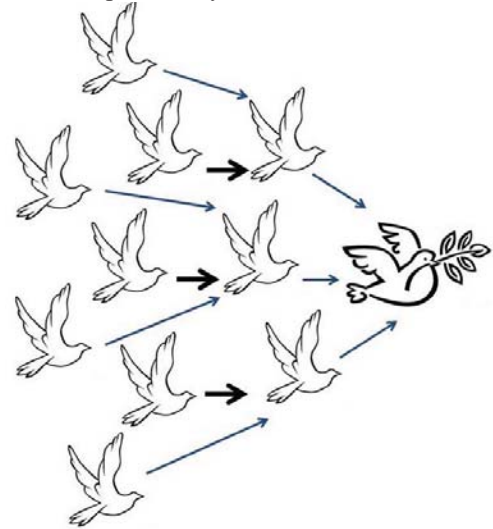


Figure 4 conditional crossover operation

As shown in Figure4, the right-centered pigeon denotes the global best position, the front three pigeons are generated by the latter three pigeons which are presented by the black thick arrows. The rest of pigeons will straightly follow the front pigeons to the global best position, which is shown in the blue arrows.

Global search performance is greatly improved on the basis of the aggregation of these two procedures. The detailed operation is presented in the following section.

##### B. Multiple UAVs mission assignment using the modified PIO algorithm

By applying the modified PIO algorithm in multiple UAVs mission assignment, we can optimize the evaluation function  $f(d, a, v)$  to obtain a better scheme. Considering that all the positions are continuous value which cannot be used to encode each UAV directly. We stipulate a certain abscissa range according to the property of each UAV which can be described as follows:

TABLE I. DISTRIBUTION RANGE

Distribu tion range	UAV number			
	1	2	3	4
Abscissa range	[0,10]	(10,20]	(20,30]	(30,40]

Pigeons in the same range will have the same properties except their coordinates. The inaccuracy of this kind of distribution can be ignored when the iteration number is large enough. Here presents the specific procedure of this method:

**Step1:** Establish the simulated scene according to the real situation and determine  $S$ ,  $T$  and  $I$ , initialize the location of every UAV and target. Here shows one of the circumstances we simulate:

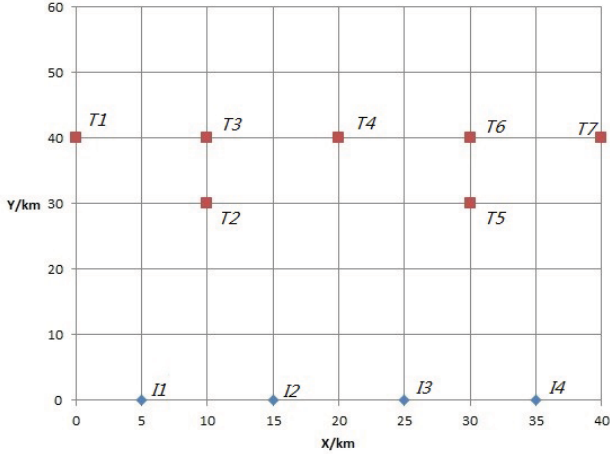


Figure 5. Scenario illustration

where the locations of blue points represent our UAV initial positions, the locations of red points denote the target initial positions.

**Step2:** Initialize all the parameters according to experiences and real situations.

**Step3:** Search for target  $T_i$ , and initialize the properties including distance, velocity, angle and range for every pair of  $I_i$  and  $T_i$ .

**Step4:** Update  $D$ -dimension position  $X_i$  and velocity  $V_i$  according to equation (9) (10) and (18) for each pigeon, calculate the evaluation function according to equation (7)

**Step5:** Select a random group of pigeons to operate the crossover amongst them and update  $X_g$  based on the new subpopulation.

**Step6:** If the cycle index  $n > Nc1$ , jump out of map and compass section and go to step7. Otherwise, go back to step4.

**Step7:** Rank all the individuals according to the evaluation function and cast the low half, update  $X_c$  and  $X_i$  of the reserved individuals according to equation (12) and (13).

**Step8:** Calculate the new evaluation function to operate the crossover and update  $X_g$  according to it.

**Step9:** If  $n > Nc2$ , jump out of landmark section and go to step10. Otherwise, go back to step7.

**Step10:** Calculate the global best position of history  $X_p$ , this position shows the best scheme of the assignment for  $T_i$ .

**Step11:** If the target  $T_i$  is the last one, reserve all the values of  $X_p$  and output the result. Otherwise, go back to step3.

## V. SIMULATION RESULTS

To verify the validity and feasibility of the modified PIO-based multiple UAVs mission assignment approach, simulation experiments are carried out and the simulation results are compared with those obtained by using modified PIO, PIO, DE and PSO based algorithm.

The properties of UAVs, including range of weapons and energy consumption constant, are given as follows:

TABLE II. VALUES OF RANGE AND C

Values of range and C	UAV number			
	1	2	3	4
range/km	50	50	40	60
C	10	10	10	10

The weight parameters are set with  $k_d=0.3$ ,  $k_c=0.4$ ,  $k_a=0.2$ ,  $k_v=0.1$ , and PIO parameters  $N_p=200$ ,  $D=4$ ,  $R=0.3$ ,  $Nc1=250$ ,  $Nc2=300$ . Some comparative patterns with PSO parameters  $w=0.5$ ,  $c1=c2=1.2$  and DE parameters  $CR=0.6$ ,  $F=0.6$  after 300 iterations at different target  $T_i$  are shown as follows:

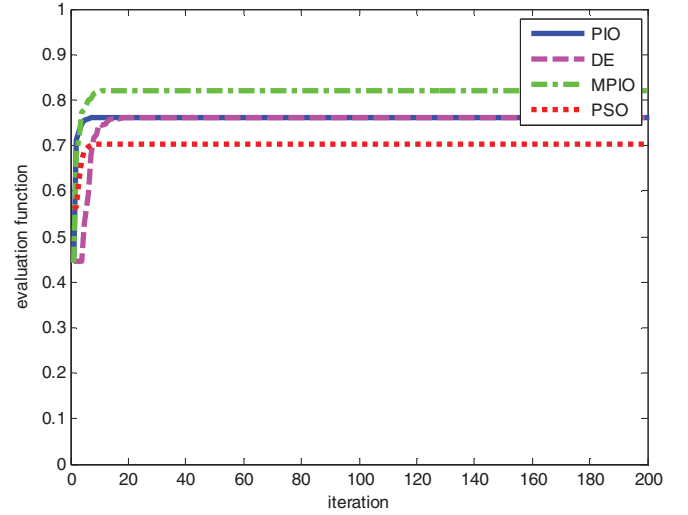


Figure 6. Comparative curve 1

where the modified PIO algorithm parameters are  $N_p=200$ ,  $D=4$ ,  $P_R=0.2$ ,  $P_C=0.2$ , at  $T_1=[0,40]$  and the maximum values of the evaluation function of modified PIO, PIO, DE and PSO are 0.821651, 0.766442, 0.766440 and 0.705326 respectively.

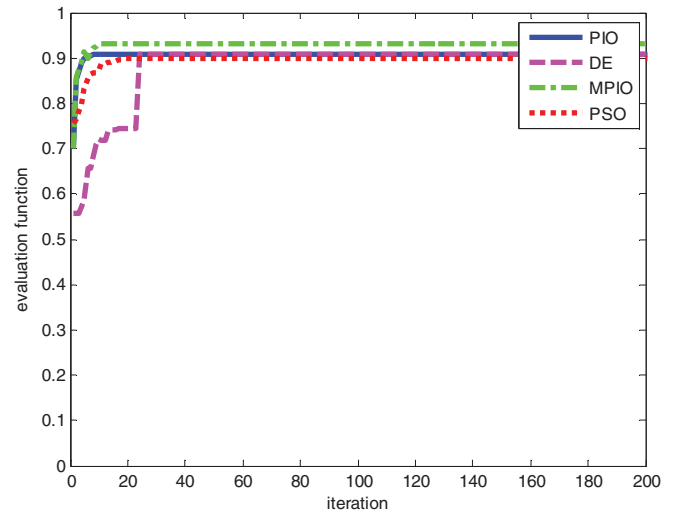


Figure 7. Comparative curve 2

where the modified PIO algorithm parameters are  $N_p=200$ ,  $D=4$ ,  $P_R=0.2$ ,  $P_C=0.2$ , at  $T_2=[10, 30]$  and the maximum values of the evaluation function of the modified PIO, PIO, DE and PSO are 0.928657, 0.902653, 0.901448 and 0.898263 respectively.

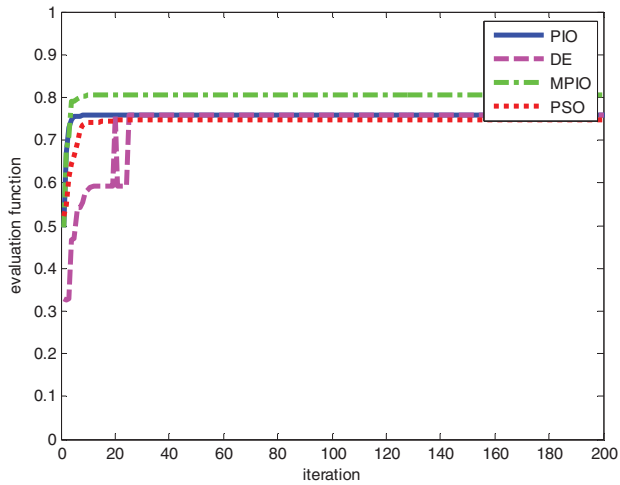


Figure 8. Comparative curve 3

where the modified PIO algorithm parameters are  $N_p=200$ ,  $D=4$ ,  $P_R=0.2$ ,  $P_C=0.2$ , at  $T_7=[40, 40]$  and the maximum values of the evaluation function of the modified PIO, PIO, DE and PSO are 0.806950, 0.762412, 0.762412 and 0.745253 respectively.

By comparing these different curves, it is easily observed that the modified PIO curves can get better evaluation functions than PIO, PSO and DE curves. The convergence speed of modified PIO curve is faster than the other algorithms. Besides, classic PIO, PSO and DE curves are easy to fall into local optimum. The simulation results show that the modified PIO procedure is more effective in handling the multiple UAVs mission assignment problem than using other algorithms.

After 100 times simulations, we can find the best solution for every target. The assignment solutions of four algorithms are presented as follows:

TABLE III. THE PIO ASSIGNMENT RESULT

The PIO assignment result	Targets						
	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$	$T_6$	$T_7$
UAV number	1	2	2	3	3	4	4

TABLE IV. THE MODIFIED PIO ASSIGNMENT RESULT

The PIO assignment result	Targets						
	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$	$T_6$	$T_7$
UAV number	1	2	1	3	3	4	4

TABLE V. THE PSO ASSIGNMENT RESULT

The PSO assignment result	Targets						
	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$	$T_6$	$T_7$
UAV number	1	1	2	2	3	3	4

TABLE VI. THE DE ASSIGNMENT RESULT

The DE assignment result	targets						
	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$	$T_6$	$T_7$
UAV number	1	1	2	2	3	3	4

UAV number	1	1	2	2	3	4	4
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## VI. CONCLUSIONS

In this paper, one type of mathematical model of multiple UAVs mission assignment is established. An evaluation function is also constructed by taking energy consumption into account. A modified PIO algorithm is applied in optimizing the evaluation function to obtain the best assignment solution. The comparative simulation results show that the modified PIO approach is more effective in solving multiple UAVs mission assignment problem than using the classic PIO, DE and PSO algorithms.

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