# Discrete Pigeon Inspired Simulated Annealing Algorithm and Contract Net Algorithm based on Multi-objective Optimization for Task Allocation of UAV Formation

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Abstract: In this paper, a mathematical model of multi-objective optimization under complex constraints is established to solve the task allocation problem. Among them, the constraint indexes include UAV quantity constraint and fuel consumption constraint; the optimization objectives include the gain, loss and fuel consumption. Discrete Pigeon Inspired Optimization-Simulated Annealing (DPIO-SA) algorithm is proposed to solve this problem. The experimental results show that while the total fitness reaches the optimum, the gain is the largest, the loss and fuel consumption are the smallest. After running the algorithm 30 times. The number of times that DPIO-SA reaches the global optimum is 15, while DPIO is 2. In addition, the average value of DPIO-SA after stabilization is 13.5% larger than that of DPIO. Both prove that after joining SA, the algorithm is easier to reach the global extremum. The Contract Net Algorithm (CNA) is adopted to solve the task scheduling problem. The UAVs are divided into tenderer UAV, potential bidder UAVs, bidder UAVs and winner UAV. After network communication, suitable bidder UAV is found to replace tenderer UAV to perform the task. Experimental results show that the algorithm has good applicability.

## 1 INTRODUCTION

Multi-Unmanned Aerial Vehicles (UAVs) cooperative task allocation is a process that multi UAVs are divided into small-scale formation and assigned to different tasks according to a set of specific constraints to achieve some optimal or sub optimal performance (Zong et al., 2017).

The mathematical model of task allocation is mainly divided into centralized model and distributed model. The centralized task allocation model includes Multi-dimensional Traveling Salesman Problem, Vehicle Routing Problem model, Multi-Dimensional Dynamic Network Flow Optimization model, Multi-dimensional Multi-choice Backpack Problem model and the improvement of related models (Chen and Qiao, 2016). Distributed task allocation includes contract net model, auction algorithm model, et al. Task allocation has been proved to be a NP hard problem (Qi et al., 2019). At present, many algorithms have been used to solve this problem, including Particle Swarm Optimization algorithm (PSO), Simulated Annealing (SA) algorithm, Tabu search algorithm and so on. In recent years, various bio-optimization algorithms have emerged, such as: Ant Colony Optimization (ACO), Artificial Fish Swarm algorithm (AFSA), Pigeon-Inspired Optimization (PIO) and so on. ACO uses information feedback mechanism to move towards a better solution through the exchange of information between individuals. But the search time is long and sensitive to initialization values. If the initial value is not selected properly, it is easy to fall into local extremum (Ratanavilisagul et al., 2017). AFSA imitates the five behaviours of the fish swarm: selection, search, swarm, follow and bulletin. It is helpful to solve real-time problems, but often cannot get accurate solutions (Zainal et al., 2015). PIO algorithm was proposed by Duan in 2014 (Duan and Qiao, 2014). At first, it is used to solve the problem



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of air robot path planning, and then it is applied to image restoration and parameter optimization (Duan and Wang, 2016; Duan and Xu, 2020). These proves that PIO algorithm has great application potential and good applicability. However, PIO algorithm is often used to deal with continuous problems, and the mining of discrete problems is not deep enough. By deeply understanding the mechanism of PSO algorithm, Ye(Ye et al, 2017) adopted the crossover and replacement operations of genetic algorithm (GA) to update the speed and position of particles, and solves the problem of task allocation. Inspired by him, this paper adopts the same form to update pigeons' state information, and realizes the discrete processing of PIO algorithm. On the other hand, at present, a single algorithm can no longer meet the needs of various problems, so it has become a general trend to merge the advantages of multiple algorithms to make up for the shortcomings of a single algorithm. In view of the advantage of SA algorithm which can keep the poor solution with a certain probability and jump out of the local extremum, this paper integrates SA in DPIO, which not only avoids the premature convergence of the algorithm, but also effectively shortens the optimization time of the algorithm.

After task allocation, if a certain UAV cannot perform the task under special circumstances, the Contract Net Algorithm (CNA) is used for task scheduling. CNA is one of the distributed task allocation algorithms, which has better scalability and robustness. It is a kind of negotiation and coordination mechanism, which simulates the economic behaviour of "tender-bid-win" mechanism to schedule tasks (Qiao et al., 2016). At present, the research of CNA has a broad basis. Chen (Chen and Qiao, 2016) adopted the CNA to study the real-time scheduling of the manufacturing system. Experiments show that the method can effectively reduce the impact of disturbance factors such as equipment failure on the system operation. Li (Li and Zhang., 2017) combines the task load rate index and token ring network in the CNA, which solves the task allocation problem of multi autonomous underwater vehicles and reduces the irrationality of task allocation. Because of the good real-time performance of CNA, this algorithm is adopted to solve the task scheduling problem.

The rest of this paper is arranged as follows: In section 2, the task allocation model is introduced; In section 3, the DPIO-SA algorithm is proposed to solve the task allocation problem; In section 4, CNA is adopted to solve the task scheduling problem; In section 5, the experimental results and simulation are listed; In section 6, conclusion.

There are two innovations in this paper. Firstly, the exchange and cross operations are used to update the state information of pigeons and realize the discretization of PIO algorithm. Secondly, Adding SA algorithm to DPIO algorithm makes it easier to jump out of local extremum.

# 2 TASK ALLOCATION MODEL

For the convenience of analysis, the variables in this paper are defined as shown in Table 1:

Table 1: Related variables in task allocation model.

| Parameter | Meaning |
|---|---|
| $U$ | Number of UAVs |
| $task\_nums$ | Number of tasks |
| ( $p_{u,i}^x$ , $p_{u,i}^y$ ) | Initial position of the $i^{th}$ UAV |
| ( $p_{t,j}^x$ , $p_{t,j}^y$ ) | Initial position of the $j^{th}$ task |
| $l_i^L$ | Lower limit of UAVs quantity required for $i^{th}$ task |
| $l_i^H$ | Upper limit of UAVs quantity required for $i^{th}$ task |
| $l_{t,i}$ | Number of UAVs performing $i^{th}$ task actually |
| $att(uav_i)$ | Attack capability of $i^{th}$ UAV |
| $def(uav_i)$ | Defensive capability of $i^{th}$ UAV |
| $att(task_j)$ | Attack capability of $j^{th}$ task |
| $def(task_j)$ | Defensive capability of $j^{th}$ task |
| $val(uav_i)$ | Importance of $i^{th}$ UAV |
| $val(task_j)$ | Importance of $j^{th}$ task |
| $fuel_{\max}$ | Maximum fuel that a single UAV can carry. |
| $fuel_{u,i}$ | Fuel consumption per unit distance |
| $\omega_1,\omega_2,\omega_3,\omega_4$ | Weights of related indexes |

## 2.1 Constraints

Using the coordinate information of the UAVs and tasks, the distance of $i^{th}$ UAV and $j^{th}$ task is calculated.

$$d_{i,j} = \sqrt{(p_{u,i}^x - p_{t,j}^x) + (p_{u,i}^y - p_{t,j}^y)} \tag{1}$$

The relationship between the fuel consumption and distance can be expressed by:

$$fuel_i = fuel_{u,i} \cdot d_{i,j} \tag{2}$$

When performing the task, we consider the UAV to be at a constant speed, so $fuel_{u,i}$ is set as a constant. Then the fuel constraint can be expressed by:

$$fuel_i \le fuel_{\max} \tag{3}$$

When assigning tasks to UAVs, the number of UAVs required for each task is different, and they need to be kept within a range. If the number is not in this range, it may affect the interaction and communication of UAVs. The number constraint of UAV required for each task can be expressed by:

$$l_i^L \le l_{t,i} \le l_i^H \tag{4}$$

Transforming this constraint into penalty can be expressed as:

$$pe = \begin{cases} \sum_{i=1}^{task\_nums} \left| l_i^L - l_{t,i} \right| & l_i^L > l_{t,i} \\ \sum_{i=1}^{task\_nums} \left| l_i^H - l_{t,i} \right| & l_i^H < l_{t,i} \\ 0 & \text{others} \end{cases} \tag{5}$$

At the same time, each task requires multi UAVs to perform together, and a single UAV can only perform one task. It can be expressed as:

$$\sum_{j=1}^{task\_nums} allo_{i,j} = 1, i = 1, 2, \cdots U. \tag{6}$$

### 2.2 Performance Indicators

The loss index of the UAV is related to the defensive ability of UAV and the attack ability of task. Similarly, the damage index of the task is related to the attack ability of UAV and the defensive ability of task, which can be expressed as:

$$los_{i,j} = att(task_j) / def(uav_i) \tag{7}$$

$$dam_{i,j} = att(uav_i) / def(task_j) \tag{8}$$

The loss of each UAV can be expressed as the product of loss index of the UAV and the importance of the UAV.

$$utlos = \sum_{j=1}^{task\_nums} \sum_{i=1}^{U} allo_{i,j} los_{i,j} val(uav_i) \tag{9}$$

The cost of fuel consumption can be expressed as the sum of fuel consumed by each UAV after running to the designated task location.

$$utfuel = \sum_{i=1}^{U} fuel_i \tag{10}$$

The gain of executing tasks is defined as the product of the damage index of the task and the importance of the task.

$$utgain = \sum_{j=1}^{task\_nums} \sum_{i=1}^{U} allo_{i,j} dam_{i,j} val(task_j) \tag{11}$$

The gain, loss, fuel consumption and penalty are integrated in the evaluation function as the total fitness. Then the evaluation function is combined with the constraints to solve the following problem:

$$\begin{aligned} \max J = {} & w_1 \cdot utgain - w_2 \cdot utlos \\ & - w_3 \cdot utfuel - w_4 \cdot pe \\ s.t. \ & \sum_{j=1}^{task\_nums} allo_{i,j} = 1, i = 1, 2, \cdots, U \\ & fuel_i \le fuel_{\max} \end{aligned} \tag{12}$$

## 3 DPIO-SA ALGORITHM

PIO is generally used to solve the continuous problem, while the task allocation problem is a discrete problem, so the form of solution needs to be rewritten. In this paper, multi-dimensional integer vector coding is adopted to represent solutions. In the result of DPIO, the vector dimension represents the UAV number, and the vector element represents the task number to be executed. For example, if the solution is 1-3-3-2-1, which means the number of UAV executing task 1 is 1,5; the number of UAV executing task 2 is 4; the number of UAV executing task 3 is 2,3.

Due to the complexity of the constraints and the large amount of calculation, the DPIO is proposed for solving.

When pigeons are far away from their destination, they will fly in a general direction according to the magnetic field and the sun. Reflected in the early stage of the algorithm, it is expressed as learning from the global optimal individual. Through in-depth analysis and research on the mechanism of the PIO algorithm, it is found that the essence of the compass operator is to use the individual's own information and the optimal individual to update the position, so we can reconstruct its update formula.

$$X_i(t+1) = c \otimes F_2 \left\{ w \otimes F_1 \left[ X_i(t) \right], p_g(t) \right\} \tag{13}$$

where, $X_i(t)$ represents the positions of pigeon group in the $i^{th}$ iteration. $p_g(t)$ represents the global extremum. $w$ represents the inertia weight. $c$ represents learning coefficient. $F_1(X_i(t))$ is the function of the influence of pigeon's own velocity on its position. $F_2(X_i(t),\ p_g(t))$ is the function that pigeons learn from global extremum.

The position update formula consists two parts. Let $\psi_i(t)$ be the temporary variable:

(i)

$$\psi_i(t) = w \otimes F_1(X_i(t)) = \begin{cases} F_1(X_i(t)), & r_1 < w \\ X_i(t), & r_1 \ge w \end{cases} \tag{14}$$

This is the inertia part of the individual, which indicates the reference of the individual to its own speed. Among them, $\psi_i(t)$ represents the pigeon's speed. During speed updating, a random number $r_1$ in the interval [0, 1] is generated by $rand()$. If $r_1 < w$, genes exchange will be perform. Two random numbers $a$ and $b$ are generated, and then the genes at $a$ and $b$ positions in the solution are exchanged, which means, the task to be performed by the $a^{th}$ UAV is exchanged with that to be performed by the $b^{th}$ UAV. As shown in Figure 1.

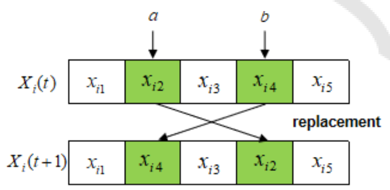



Figure 1: Schematic diagram of exchange operation.

(ii)

$$X_i(t+1) = c \otimes F_2(\psi_i(t), p_g(t)) = \begin{cases} F_2(\psi_i(t), p_g(t)), & r_2 < c \\ \psi_i(t), & r_2 \ge c \end{cases} \tag{15}$$

This is the learning part of the individual, which indicates that the pigeon adjusts its position according to the global extremum $p_g(t)$. During learning, a random number $r_2$ in the interval [0, 1] is generated by $rand()$. If $r_2 < c$, genes cross will be performed. Two random numbers $a$ and $b$ are generated, and then the genes between $a$ and $b$ positions in the solution are exchanged by global extremum $p_g(t)$, which means, the tasks performed by the $a^{th}$ to the $b^{th}$ UAVs are all replaced by the tasks performed by the $a^{th}$ to the $b^{th}$ UAVs in the global extremum $p_g(t)$. As shown in Figure 2.

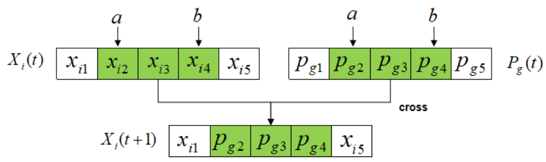



Figure 2: Schematic diagram of cross operation.

When the pigeon group is close to the destination, it will be closer to the population that is familiar with the landmark information. After each iteration, the number of pigeon population will be halved, and the first half with better adaptability will be selected as the current population. The center of the remaining pigeon group is obtained by averaging the genes in the remaining pigeon group, and the center is used as the reference direction to update the position of each pigeon. The operation is as follows:

$$N_p(t+1) = \frac{N_p(t)}{2}$$

$$X_c(t+1) = round\left( \frac{\sum_{i=1}^{N_p(t+1)} X_i(t+1)}{N_p(t+1)} \right) \tag{16}$$

$$X_i(t+1) = d \otimes F_2\left[X_c(t+1)\right]$$

When the position is updated, a random number $r_2$ is generated by $rand()$. If $r_2 < d$, two random numbers $a$ and $b$ are generated. Then the genes between $a$ and $b$ of the current individual are replaced by the genes of the reference center.

However, DPIO is easy to fall into local extremum. In order to solve this problem, SA is used to improve it. The main idea of SA is to judge whether to accept new solution according to the Metropolis criterion. The metropolis guidelines are as follows:

$$y = \begin{cases} 1, & \Delta > 0 \\ \exp(\Delta / T), & \Delta \le 0 \end{cases} \tag{17}$$

where $\Delta = fitness(new) - fitness(old)$.

The specific method is: after each iteration of compass operator and landmark operator, the fitness of the new solution and the current solution is compared. If the fitness of new solution is higher, the new solution is accepted; Else, a random value $r_3 \in [0,1]$ is generated. If $r_3 < y$, the new solution is accepted, otherwise the solution is not updated.

The flow chart of DPIO-SA is shown in Figure 3.

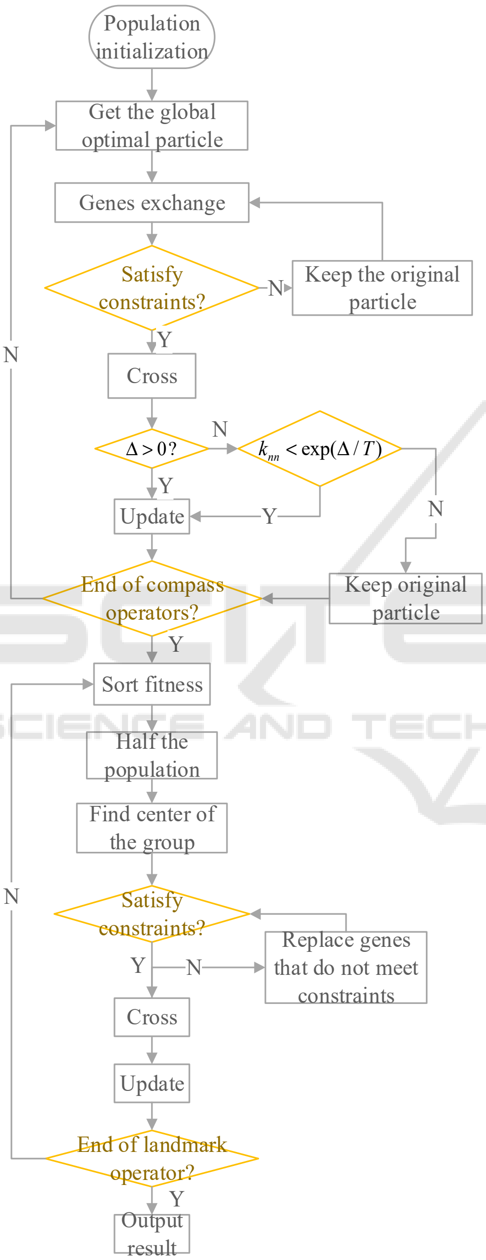



Figure 3: Flow chart of DPIO-SA algorithm.

## 4 CONTRACT NET ALGORITHM

In the CNA, UAVs are divided into the tenderer UAV, the potential bidder UAV, the bidder UAV and the winner UAV. The tenderer UAV is the owner of the task; The potential bidder UAV is the UAV that have a communication relationship with the tenderer UAV and the bidder UAVs are the UAVs that meet the task constraints. The winner UAV is the UAV that finally signs the contract with the tenderer UAV after bidding.

When a UAV is unable to perform the current task due to special circumstances, the CNA is used for task scheduling. First, whether the task performed by the UAV meet the UAV quantity constraint is judged. If it is not satisfied, i.e. $l_{t,i} < l_i^L$, then the UAV will issue tasks as the tenderer UAV. Then, the tenderer UAV issues tasks to the UAVs that have communication relationship with it. These UAVs are defined as potential bidder UAVs.

Next, in the bidding stage, the potential bidder UAV first judges whether there are redundant UAVs in the currently executed task. If not, the UAV cannot perform other tasks; if there are, then, it is judged whether the UAV meets the fuel constraint from its position to the task assembly point of the bidder's UAV, if so, it will be marked as the bidder UAV. And the *gain*, *utlos* and *utfuel* will be used as performance indicators to calculate the overall capacity and send it to the tenderer UAV.

$$J_2 = w_1 \cdot utgain - w_2 \cdot utlos - w_3 \cdot utfuel \qquad (18)$$

Finally, the tenderer UAV selects the bidder UAV with the largest overall capacity according to the returned information and sends winning information to it. After receiving the information, the winner UAV changes its task attributes and executes the task assigned to the tenderer UAV. The specific negotiation process is shown in Figure 4:

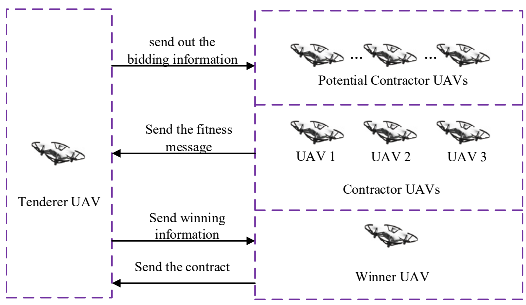



Figure 4: Task negotiation process based on CAN.

# 5 EXPERIMENT SIMULATIONS

In order to verify the effectiveness of the algorithm, the simulation experiments are carried out under the Windows 10 operating system based on Matlab2019 (a) environment.

## 5.1 DPIO-SA Experiment Results

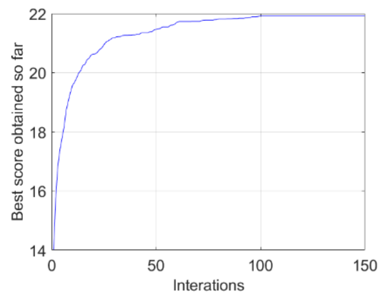
After running the program, we can get the value range of gain is [6.1235, 6.7347], the value range of loss is [29.6690, 36.1274], and the value range of fuel consumption is [480.5009, 721.3119]. In order to ensure that the length of the three values are the same, let $w_1 = 10$, $w_2 = 1$, $w_3 = 0.025$ . In order to ensure that the task allocation results meet the quantity constraints, $w_4$ must be large enough, so $w_4$=1000 . The number of the number of simulated pigeons is $n = 100$ . The number of compass iterations is $Dt_1 = 100$ The number of landmark iterations is $Dt_2 = 50$ .The initial temperature of SA is $T = 8$ , the temperature attenuation factor is $k = 0.8$ , The number of SA iterations is $L$=30 . The UAVs are randomly distributed in the site of $100m \times 100m$ .The number of UAVs used in the experiment is 24, and each task target is at the quintile of the site. Due to the excessive number of UAVs, their performance parameters are too large, which will not be listed here. Task performance parameters are shown in Table 2.

Table 2: Task parameters.

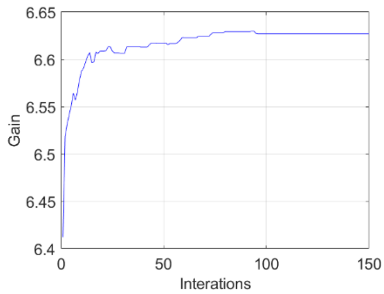
| | Task1 | Task 2 | Task 3 | Task 4 | Task 5 |
|---|---|---|---|---|---|
| x | 25 | 50 | 25 | 75 | 75 |
| y | 25 | 50 | 75 | 25 | 75 |
| A | 54 | 72 | 46 | 54 | 54 |
| D | 77 | 68 | 42 | 77 | 77 |
| V | 0.45 | 0.15 | 0.25 | 0.45 | 0.45 |
| $l_i^L$ | 4 | 4 | 4 | 4 | 4 |
| $l_i^H$ | 8 | 9 | 9 | 8 | 8 |

where (x, y) is the position of tasks, A and D are the attack and defensive ability of the tasks, respectively. V is the value of the tasks.

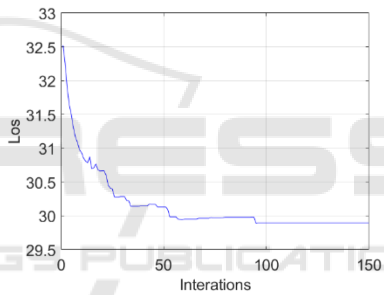
Run the program 30 times to find the average value of each parameter. The iteration results of each indicator of task allocation are shown in the figure 12:



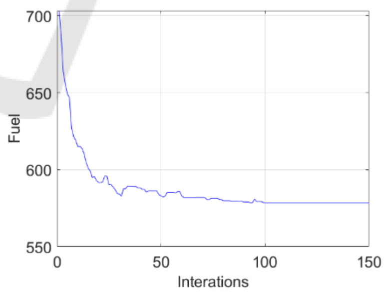

(a) Total fitness




(b) Gain




(c) Loss




(d) Fuel consumption

Figure 5: Results of task allocation.

where Fig 5(a) shows the total fitness, Fig 5(b) shows the gain. Fig 5(c) shows the loss, Fig 5(d) shows the fuel consumption. It can be seen from the Figure 5 that the algorithm converges after 103 iterations in average, and we can see that while ensuring the total fitness is maximized, the gain is maximized, the loss and the fuel consumption are minimized.

The algorithms based on DPIO and DPIO-SA are simulated. Take the average values of the algorithms after 30 runs. The comparison is shown in Figure 6.

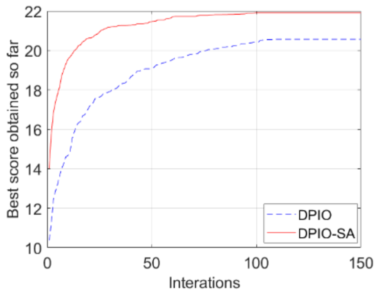



Figure 6: Comparison of DPIO and DPIO-SA.

As can be seen from the Figure 6, the average convergence value of DPIO-SA is 21.9444, and DPIO-SA is 20.5672. In order to better compare the two algorithms, a baseline is set, here we set it as the minimum fitness during the execution of the algorithm. Therefore, the following formula can be used for comparison:

$$\eta = \frac{\Delta_{fitness}}{fitness_{DPIO} - base} \tag{19}$$

where $\Delta_{fitness} = fitness_{DPIO-SA} - fitness_{DPIO}$, $base = 10.3712$. It can be concluded that the convergence value of DPIO-SA is 13.5% higher than that of DPIO. At the same time, in 30 runs, the number of times DPIO-SA reaches the global extremum is 15. And DPIO is 2. Both mean DPIO-SA is easier to jump out of local extremum.

The optimal solution of the task allocation is shown in the Table 3:

Table 3: Results of the task allocation.

| Task number | UAV number |
|---|---|
| 1 | 1-6-7-22 |
| 2 | 5-14-16-21 |
| 3 | 8-9-10-17-18 |
| 4 | 2-3-11-12-20 |
| 5 | 4-13-15-19-23-24 |

## 5.2 CNA Experiment Results

First, a UAV is randomly selected as the tenderer UAV release the task. Assume that the tenderer UAV is UAV6. From the task allocation result, UAV6 performs task1. The lower limit of the number of UAVs required for task1 is $l_1^L = 4$, so when UAV 6 fails to perform task1, the task cannot be completed. At this time, the CNA is used for task scheduling.

Firstly, UAV6 issues task to all UAVs in the network. Because of the large number of UAVs, the UAV communication diagram is represented by task network. When there is a connection between two tasks, it means that all UAVs between the two tasks can communicate with each other. The task networking diagram of this paper is shown in Figure 7:

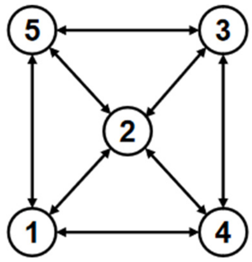



Figure 7: The task network diagram.

It can be seen from Figure 7 that tasks associated with task 1 include task 3, task 4, and task 5. According to the task allocation result, all UAVs performing task 3, task 4, and task 5 have redundant UAVs, so all UAVs performing these three tasks will be considered as potential bidder UAVs. According to whether the fuel constraints between UAVs and task1 are met, the potential bidder UAVs can be considered as bidder UAVs. The fitness is calculated according to the contract, as shown in Table 5. After bidding, the winner UAV is UAV 17. The types of UAVs in the CNA are shown in Table 4.

Table 4: Types of UAVs in the contract network.

| Potential Bidder UAVs | Bidder UAVs | Winner UAV |
|---|---|---|
| UAV2, UAV3, UAV4, UAV8, UAV9, UAV10, UAV11, UAV12, UAV13, UAV15, UAV17, UAV18, UAV19, UAV20, UAV23, UAV24 | UAV2, UAV11, UAV13, UAV17, UAV20 | UAV17 |

Table 5: Bidder UAVs and corresponding fitness.

| UAV number | Fitness |
|---|---|
| UAV 2 | 20.9041 |
| UAV 11 | 21.1804 |
| UAV 17 | 21.4688 |
| UAV 13 | 21.093 |
| UAV 20 | 21.3611 |

# 6 CONCLUSION

In this paper, aiming at the problem of multi-UAV task allocation, a mathematical model for multi-objective optimization under complex constraints is established, and DPIO-SA algorithm is proposed to solve it. Firstly, the speed and position information of the pigeon group are changed according to the exchange and cross operations, which solves the difficulty of the PIO algorithm to deal with the discrete problem. Then, after each iteration, the SA algorithm is used to judge whether to accept the new solution or not, which makes the algorithm easier to jump out of the local extremum. The experimental results show that when the overall performance index reaches the optimum, the profit value reaches the maximum and the loss and fuel consumption reach the minimum. After run the algorithms 30 times, it can be seen clearly that DPIO-SA has better optimization ability than DPIO. Aiming at the task scheduling problem, this paper proposes the CNA to get the optimal task scheduling scheme through four stages: First, the tenderer UAV sends out bid information to potential bidder UAV. Then, the potential bidder UAV is screened out as the bidder UAV according to the contract requirements, and the fitness information is sent to the tenderer UAV. Then, the tenderer UAV selects the appropriate bidder UAV as the winner UAV and sends the winning information. Finally, the tenderer UAV and the winner UAV sign the contract.

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