

# On-Orbit Servicing Mission Planning for Multi-spacecraft Using CDPSO

Jianxin Zhang<sup>(✉)</sup>, Ying Zhang, and Qiang Zhang<sup>(✉)</sup>

Key Lab of Advanced Design and Intelligent Computing, Dalian University,  
Ministry of Education, Dalian 116622, China  
zjx99326@163.com, zhangq26@126.com

**Abstract.** Spacecraft mission planning can improve the collaborative work efficiency of the on-orbit servicing (OOS) spacecrafts. A chaos discrete particle swarm optimization (CDPSO) algorithm is applied according to the characteristics of multi-spacecraft collaborative mission planning problem. We design the new update formulae of position and velocity of the particles for the OOS optimization mission. By analyzing the critical index factors which contain the value of the target spacecrafts, the attrition of servicing spacecraft and consumption of time and fuel during the process of service, a mathematical model is formulated. Simulation results show that the algorithm can solve the multi-spacecraft mission planning problem under multiple constraints efficiently. It is expressive, flexible, extensible and feasible easily.

**Keywords:** On-orbit servicing · Spacecraft mission planning · Discrete particle swarm optimization · Chaos

## 1 Introduction

The on-orbit servicing (OOS) technology is the use of automated technology and robot technology for the on-orbit inspection, repair, refueling, upgrade, maintenance, assembling and release by the use of automation and robotics [1, 2]. The OOS technology can effectively prolong the life of spacecraft and reduce the costs. However, the carrying capacity of space vehicle is strictly limited. Spacecraft mission planning algorithms can improve the collaborative work efficiency of OOS, which makes them widely studied in many military developed countries.

With the maturity of OOS, it will be developed to a systematic way, and set up an OOS system which cooperative service by multiple on-orbit spacecraft [3]. In Ref. [4], the mathematical model of long-range maneuver transfer with impulse thrust is analyzed. It considers the time and energy cost and uses EDA to optimize. However the capability of single spacecraft is limited and multi-spacecraft cooperation is drawing more and more attention [5]. This paper presents a chaotic discrete particle swarm (CDPSO) algorithm for the multi-constrained problem about value of the target spacecrafts, attrition of servicing spacecraft and consumption of transfer time and fuel using Lambert two-impulse orbital transfer with unfixed transfer time. The algorithm combines the chaos algorithm with the discrete particle swarm optimization (DPSO) algorithm.

## 2 Problem Description

The scenario and transfer process of OOS planning studied in this paper is shown in Fig. 1. The target spacecraft and the servicing spacecraft run in the predefined orbits respectively. If an OOS request is issued, a suitable Lambert double pulses orbit transfer to the target track would implemented from the servicing spacecraft maneuvers to the target spacecraft immediately to conduct the required OOS operation. Thus the servicing satellite is reusable [6].

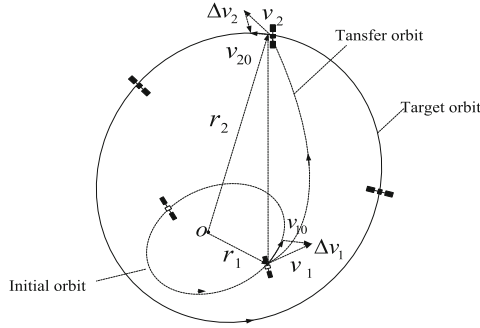


Fig. 1. Sketch of Lambert transfer

## 3 Mathematical Models

### 3.1 Decision Variables

Assuming  $N$  servicing spacecrafts on-orbit are deployed, and  $M$  different task priority target spacecrafts waiting for service at a given time, according to the characteristics of the planning problem, the decision variables can be defined as follows:

$$x_{nm} = \begin{cases} 1, & \text{assigned } n \text{ to } m \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where  $n = 1, 2, \dots, N; m = 1, 2, \dots, M$ . Thus, important performance indicators for measuring the pros and cons of the multi-spacecraft collaborative mission planning program are mainly included the following three parts in this paper [7–9].

### 3.2 Service Spacecraft's Consume Indicators

The value of attrition for servicing spacecraft  $N$  to serve target spacecraft  $M$  is  $a_{nm}$ , and  $1 - a_{nm}$  represents its remaining service capacity. The objective is to find a feasible target assignment to minimize servicing spacecraft attrition. The problem can be formulated as follows:

$$\min \sum_{n \in N} \sum_{m \in M} a_{nm} x_{nm} \quad (2)$$

### 3.3 Target Spacecraft's Value Indicators

We use  $E$  to represent the value of target spacecraft. We use  $P_c$  as the probability of the above movement. The value can be expressed as  $E_{nm} = E \bullet P_c \bullet (1 - a_{nm})$  when we provide services for target spacecraft  $m$  with servicing spacecraft  $n$ . The specific formula can be defined as follows:

$$\max \sum_{n \in N} \sum_{m \in M} E_{nm} x_{nm} \quad (3)$$

### 3.4 The Optimal Time and Fuel Consuming Indicators

Reasonable phasing maneuver can reduce energy and time consumption. Considering the fuel consumption and the transfer time, we establish the performance indicator which makes the weighted sum of energy and time minimized, i.e.

$$\min \sum_{n \in N} \sum_{m \in M} [k(|\Delta v_1| + |\Delta v_2|) + (1 - k)t] x_{nm} \quad (4)$$

where,  $\Delta v_1$  is the velocity increment required for the initial rendezvous moment,  $\Delta v_2$  is velocity increment required for terminal rendezvous moment,  $0 \leq k \leq 1$  is the proportionality coefficient. The energy consumption required for Lambert double pulse orbital maneuvering can be calculated according to rendezvous orbit time. The calculation method of  $\Delta v_1$  and  $\Delta v_2$  is described in Ref. [10].

### 3.5 Objective Function and Constraints

Through the above analysis, multi-objective function for multi-spacecraft collaborative mission planning is established. Therefore, the method of weighted summation can be used to convert multi-objective decision problems to single-objective optimization problem. Due to the different dimensions of each objective function, dimension conversion is required. We transform each dimension into the value between 0 and 1, set the value of target spacecraft  $E$  between 0 and 1, and let  $\Delta V_{nm} = \Delta v_{nm} / \Delta v_{\max}$ ,  $T_{nm} = t_{nm} / t_{\max}$ . In summary, servicing spacecraft task allocation model is as follows:

$$\max \sum_{n \in N} \sum_{m \in M} (\omega_1 \bullet E_{nm} - \omega_2 \bullet a_{nm} + \omega_3 \bullet T_{nm}) x_{nm} \quad (5)$$

where,  $\omega_1, \omega_2, \omega_3$  are weight coefficients which represent the importance degree of each sub-objective functions. Multi-spacecraft mission planning should satisfy the following constraints:

- (1)  $\sum_{n=1}^N x_{nm} = 1$ , target spacecraft can only accept one servicing spacecraft's service.
- (2) For each target spacecraft, no matter what way the service is, income of the target value is not greater than the value of the target spacecraft  $\sum_{n=1}^N P_c \bullet (1 - a_{nm}) \bullet E \bullet x_{nm} \leq E_m$ .

## 4 Hybrid Discrete Particle Swarm Optimization Algorithm

### 4.1 Discrete Particle Swarm Optimization

In this paper, the natural number coding mode is used. The length of each particle is equal to the total number of target spacecrafts. For example, the number of servicing spacecraft  $n$  is 5, the number of the target spacecraft  $m$  is 10, so a particle is represented as

Particle	2	3	4	1	3	5	4	2	3	1	Serving spacecraft number
	1	2	3	4	5	6	7	8	9	10	Target spacecraft number

According to the characteristics of multi-spacecraft collaborative task allocation problem, the position and velocity update formula of PSO can be defined as [11].

$$X_i(t+1) = c_2 F_3(c_1 F_2(w \bullet F_1(X_i(t))), p_{best}(t), g_{best}(t)) \quad (6)$$

where  $X_i$  is the position of the particle  $i$ ;  $p_{best}$  is the best previous position,  $g_{best}$  is the position of the best particle in current swarm, and  $w$  represents inertia weight of the current iteration. Cognitive parameter  $c_1$  is defined to adjust the flight step length of  $p_{best}$ , and social parameter  $c_2$  is adopted to adjust the flight step length of  $g_{best}$ .  $F_1(X_i(t))$  is the influence function for particle  $X_i(t)$ ,  $F_2(X_i(t), p_{best}(t))$  is the learning operation of  $X_i(t)$  to  $p_{best}(t)$  and  $F_3(X_i(t), g_{best}(t))$  is the learning operation of  $X_i(t)$  to  $g_{best}(t)$ . For inertia weight, we use linearly decreasing strategy as in reference [12], i.e.

$$w = (\omega_i - \omega_e)(period - t)/period + \omega_e \quad (7)$$

where parameter  $t$  is the current number of iteration,  $period$  is the largest number of iteration,  $\omega_i$  is the initial inertia weight value, and  $\omega_e$  is the inertia weight value when particles evolve to the largest number of iterations. The position updating formula can be divided into three parts as in reference [16].

### 4.2 Improved Discrete Particle Swarm Algorithm Combined with Chaos

The nature of chaos is random and unpredictable apparently, and it also possesses an element of regularity [13]. Due to the ergodicity of chaos, chaos optimization algorithm is easy to jump out of local optima, which is precisely to overcome the shortcoming of discrete particle swarm optimization (DPSO). One chaos discrete particle swarm optimization (CDPSO) algorithm based on Logistic map is proposed in this paper,

which combines DPSO and chaos theory [14]. Here, chaos variables are obtained by the Logistic mapping method [15]. Its equation is as follows.

$$z_{n+1} = \mu z_n (1 - z_n) \quad (8)$$

where  $\mu > 3.57$  and  $z_n \notin \{0.0, 0.25, 0.5, 0.75, 1.0\}$ . When  $\mu = 4$ , Eq. (8) produces a status of the pseudo-random distribution which is a completely chaotic state.

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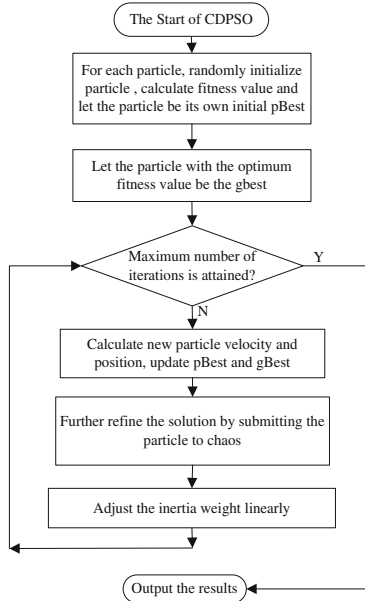
$$Z' = (1 - \beta)\Psi^* + \beta Z \quad (9)$$

where  $\beta$  distributed in the interval  $[0, 1]$  is an adjustment parameter.  $Z'$  is a chaotic variable that obtained by adding a small disturbance to the current optimal solution variable  $X^*$ .  $Z$  is a chaotic variable obtained by Logistic mapping.  $\Psi^*$  is the optimal chaotic variable obtained by the current optimal solution variable  $X^*$  mapping to  $[0,1]$ ,

$$\Psi^* = (X^* - X_{\min}) / (X_{\max} - X_{\min}) \quad (10)$$

#### 4.3 Implementation Process of On-Orbit Servicing Spacecraft Mission Planning Based on CDPSO

Flowchart of the CDPSO algorithm is shown in Fig. 2.



**Fig. 2.** Flowchart of chaos discrete particle swarm algorithm

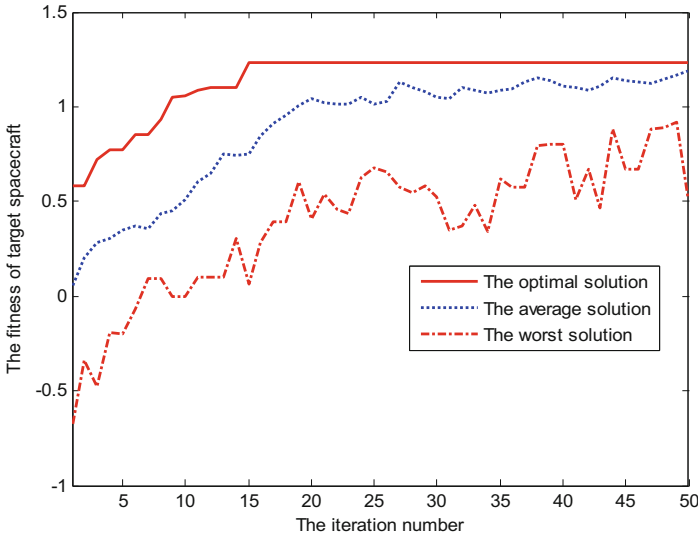
The following two points are the additional supplements to the flowchart:

- (1) Calculate the position of the new particles according to Eq. (6).
- (2) Utilize the chaos to downsize the solution and optimize the optimum position  $g_{best}$  by chaos according to Eqs. (8), (9) and (10). First, we map  $g_{best}$  to  $Z_i$  which is located in interval  $[0,1]$ . Then, we produce the chaotic sequence using Logistic equation and convert the chaotic variables to the original solution region. Finally, we evaluate the new solution and choose the best solution.

## 5 Simulation

Several experiments were carried out to demonstrate the improved algorithm. In order to compare with the models and algorithms in Ref. [16], partial data of Ref. [16] are adopted. The following assumptions are made in this allocation problem. (1) Remaining service capacity by assigning the  $n$ th servicing spacecraft to serve the  $m$ th target spacecraft is given. (2) The value of target spacecraft  $m$  is  $E$ . (3) Service probability certainty  $P_c$  is 1. (4) The initial orbital parameters of each spacecraft are known. (5) Time constraint is 3000 s. (6) The time of orbital maneuver is set in 1000~3000. Then, parameter values of CPSO are set as initial population size = 50, inertia weight  $\omega_i = 0.9$ ,  $\omega_e = 0.2$ ; (3)  $c_1 = 0.5$ ,  $c_2 = 0.5$ , and  $\beta = 0.39$ .

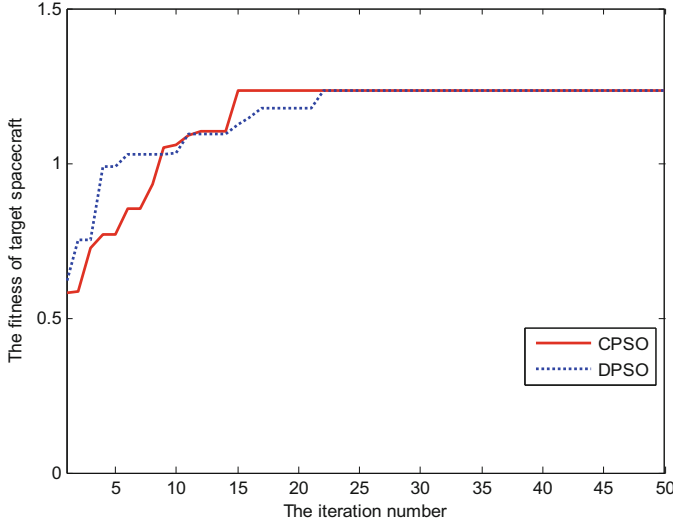
For this scenario, we used DPSO and CDPSO to simulate the above question respectively, and compared their simulation results. Figure 3 shows the fitness change of the best assignment, the average assignment and the worst assignment in 50 iterations based on improved CDPSO. The x axis is the iteration number and the y axis is the fitness of particles. Table 1 represents the ultimate performance comparison results of the servicing spacecraft task allocation between DPSO and CDPSO.



**Fig. 3.** Convergence curve of CDPSO

**Table 1.** Two algorithms' performance comparison

	DPSO	CDPSO
Optimal solution	1.2365	1.2365
Average solution	1.2190	1.2294
Worst solution	1.1691	1.1999
Convergence generation	22	15
Optimal allocation result	[2,4,4,2,4,1,2,3,2,4]	[2,4,4,2,4,1,2,3,2,4]

**Fig. 4.** Algorithm performance comparison

The convergence rate of the two algorithms and the performance of solution in Fig. 4, we know that the convergence behavior of CDPSO is better than DPSO, and it can quickly find the optimal solution. From the solution set of CDPSO changed with iterations number, it has converged to the optimal solution direction of less evolutionary generation, and this indicates that it has a higher optimize efficiency. From the curve of CDPSO with average solution, we can see that there is no phenomenon of convergence of all particles even in the late iteration stage. It enables the algorithm to continue to maintain strong optimization ability.

## 6 Conclusion

In spacecraft cooperative control, proper allocation of tasks is of great importance for the efficient utilization of the resources. The algorithm makes full use of local search ability of DPSO and global search ability of chaos, which makes the two algorithms get effective complementary and fast converges to the optimal solution, and significantly improves the performance of the algorithm. The simulations show that CDPSO is

capable to solve on-orbit servicing spacecraft mission planning. The algorithm is simple, flexible and easy to implement and extend. It can quickly find the optimum allocation scheme. However, on-orbit service mission planning is a complex problem, and we will consider more factors in the future work.

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