On-orbit Servicing Mission Planning for Multi-spacecraft Using Improved QPSO Algorithm

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Abstract

The on-orbit servicing mission assignment is very important to improve the cooperative work ratio of the on-orbit servicing spacecraft. One mission of on-orbit servicing can be fulfilled in many ways， and proper mission assignment must be guaranteed. Based on the characteristics and technical specifications of the mission planning issues, a multi-objective quantum-behaved particle swarm optimization based on QPSO and non-dominated sorting (Improved QPSO) is proposed. Since improved QPSO has the characteristic of both QPSO, which has fast convergence rate and accurate convergence value and non-dominated sorting, used to obtain non-dominated solutions, it is used to solve spacecraft task allocation. By analyzing the critical index factors which contain target spacecraft value, task completion time and distance consumption, an on-orbit spacecraft task allocation model is formulated. The best plan was achieved by Pareto optimal sets and ideal solution can be chose as necessary. Finally the example of simulation was given, it compared with another algorithm. Simulation results show that the improved QPSO has fast convergence and better distribution.

Keywords

On-orbit servicing (OOS), Spacecraft mission planning, Improved QPSO algorithm.

1. Introduction

With the deepening of space research, the structure and composition of the spacecraft is getting more complicated. Their performance and technical level is also rising. Due to the influence of the complex space environment, spacecraft is prone to failure leading to breakdown, degradation or abandoned in the long run. Re-launching replacement spacecraft not only need workable time but also lead to doubling costs. The existence of these problems will enable the on-orbit services technology to become a new and independent research direction[1-2].

The space on-orbit server technology has been one of the highlights of the space activities, which may achieve capacity extension and lifetime extension of the satellites, space launch vehicle and space station subsidiary compartment of the space assembly as well as maintenance. It may fundamentally change the spacecraft's design pattern, affect the entire aerospace infrastructure, and also be able to reduce the consumption of the entire life cycle of spacecraft greatly[3-4]. At the beginning of 21st century, the United States in space technology autonomous orbit servicing major research program has XSS program and the "Orbital Express" program[5]. The XSS program already announced XSS-10, XSS-11 and XSS-12 which are involved in OOS. In 2007, Orbital Express completed all tasks, which comprehensive validation unmanned autonomous on-orbit service multiple items, marking a breakthrough in OOS of independent key technologies, thereby to practical engineering.

From the perspective of multi task demands, the number of service spacecraft is usually less than the number of target spacecraft, so it has a variety of service options. In order to seek the maximum benefit, we must carry on the reasonable task plan from comprehensive evaluation which contained time, Fuel Consumption and value. At present, the on-orbit mission planning has already carried out some related researches both at home and abroad. Zhang[6] presented new update formulae of position and velocity of the particles, and proposed a collaborative target allocation method about multi-service spacecraft based on discrete particle swarm optimization, but he adopted a method which converted multi-objective problem into single objective problem to solve collaborative task allocation problem. The objective of task allocation which included target maximum damage and own minimum consumption was founded in the paper of Cruz Jr[7], but it reckon without the key indicator of the task time-consuming. Hu[8] created an energy-time model of two-impulse long-range rendezvous, but two factors of the spacecraft including energy and time consumption were considered merely in this paper, the range of research limited to a spacecraft.

According to the characteristics of collaborative task allocation problem of the on-orbit servicing spacecraft, this paper proposed multi-spacecraft mission planning method based on QPSO and non-dominated sorting. The paper firstly analyzed three indicators, and respectively established the value of the target spacecraft maximum model, fuel Consumption loss minimization model and the shortest time-consuming of the task model. Then, improved QPSO is used to solve the multi-objective optimization problem, and get Pareto optimal collection of solutions for this problem.

2. Problem Description

The mission scenarios and transfer process of OOS spacecraft run on the predefined tracks separately. Target spacecraft with different values are operating on a known orbit. After receiving the OOS command, on-orbit service spacecraft transfers from its preparation orbit to service orbit that close to the target spacecraft by Lambert double pulse orbit maneuver. The service spacecraft that is active needs to choose one to one service from the passive target spacecraft. Aiming at optimizing the overall revenue of the entire spacecraft formation, Multi-spacecraft mission planning is to choose service goals for each spacecraft in a task according to the planning rule of a high efficiency and lower power consumption and the service principles that the high-priority target spacecraft gets prior service.

3. Multi-objective Optimization Model

3.1 Decision variables

Decision variables determine which servicing spacecraft is assigned to which target spacecraft. Assuming that the number of the service spacecraft on-orbit that are deployed is N, and the target spacecraft whose number is M with different task value waiting for service at a given time. Then the service spacecraft provide services to the target spacecraft after receiving the service order. According to the characteristics of the planning problem, the decision variables can be defined as follows:

$$x_n = \begin{cases} m, & n \text{ serves } m \\ 0, & n \text{ doesn't serve } m \end{cases} \quad n = 1, \cdots, N;\ \mathrm{m} = 1, \cdots, M. \tag{1}$$

3.2 Objective Function

The objective function of on-orbit servicing mission assignment problem is determined according to the specific task requirements, but it can be summarized mainly include the following three parts.

(1) Task Priority

Generally, in the on-orbit spacecraft should firstly serve the target spacecraft with high value. We define P to represent target spacecraft's value, and the higher value means earlier service. First of all, the task of service spacecraft is to search and find target spacecraft in the service area. The basis of task is to find and identify target spacecraft accurately, and Pc was defined to represent the probability of the above movement. The task value can be expressed as $P_{nm} = P \bullet P_c$ when the n-th service spacecraft provides service for the m-th target spacecraft. Then the task values of each spacecraft to finish their tasks can be formulated as Eq (2).

$$Y_1 = \max \sum P_{nm} x_n \tag{2}$$

(2) Task Completion Time

In contrast with the former time, the latter service execution time is extremely short in order that can be ignored. So the task completion time can be approximated as the time of arrive at target spacecraft. The objective function considered the last task completion time. So the shortest time-consuming models can be expressed as Eq (3):

$$\Delta T = \max\left\{x_n \Delta t_{nm}\right\} \tag{3}$$

Where Δt_{nm} is the time of the n-th service spacecraft serves the m-th target spacecraft. Then the objective function can be formulated as Eq (4):

$$Y_2 = \min \Delta T \tag{4}$$

(3) Fuel Consumption

When spacecraft is in service, the objective function is the function of the fuel consumption loss minimization owing to the limitation of fuel. In this paper, the fuel consumption of orbit's maneuvering was only considered and fuel consumption can be measured by the speed of orbital maneuvering, using as the velocity increment of the n-th service spacecraft serves the m-th target spacecraft. In summary, the fuel consumption can be expressed as Eq (5):

$$Y_3 = \min \sum x_n \Delta v_{nm} \tag{5}$$

When the above solutions are to achieve the optimal, It is the ideal of service solution, when the above solutions are to achieve the optimal. Therefore the problem of mission planning can be attributed to multi-objective optimization problem.

3.3 Constraints

(1) Time constraints on mission

In this paper we use the mission completion time as a objective function therefore, In order to get the time of orbital maneuvering is too long, it's necessary to limit the maximum value of mission completion time.

$$t_f \le T \tag{6}$$

Where T is the allowing maximum time, and t_f represents the time when the task is finished.

(2) The maximum velocity increment constraints

The velocity increment of spacecraft performing the tasks must less than the maximum speed increment which can be offered. The constraint is described as follows:

$$\Delta v_{nm} \le \Delta v_n \tag{7}$$

Where Δv_n represents the maximum speed increment that the spacecraft can offer, and Δv_{nm} represents the needed speed increment.

In conclusion, the task assignment of the final mathematical model can be defined as:

$$\begin{cases} Y_1 = -\max \sum P_j x_i \\ Y_2 = \min \Delta \mathrm{T} \\ Y_3 = \min \sum x_i \Delta v_{ij} \end{cases} \tag{8}$$
$$\begin{cases} s.t. \quad t_f \le T \\ \qquad \Delta v_{ij} \le v_{\max} \end{cases}$$

4. Improved quantum particle swarm optimization

4.1 QPSO for discrete multi-objective

Since there is no published work to deal with discrete optimization problem by using a single quantum rotation gate simulation, we cited simple quantum particle swarm optimization for discrete optimization problems[9-10].

In the quantum particle swarm optimization, the evolution of quantum is the process of the renewal of the quantum velocity which is defined as a string of quantum bits. One quantum bit is defined as the smallest unit of information in the QPSO[9], which is expressed as a pair of composite numbers (α, β), where $|\alpha|^2 + |\beta|^2 = 1$. $|\alpha|^2$ gives the probability that the quantum bit will be found in the “0” state and $|\beta|^2$ represents the probability which the quantum bit will be found in the “1” state. The quantum velocity of the i-th quantum particle is defined as

$$v_i = \begin{bmatrix} \alpha_{i1} & \alpha_{i2} & \dots & \alpha_{iR} \\ \beta_{i1} & \beta_{i2} & \dots & \beta_{iR} \end{bmatrix} \tag{9}$$

Where $|\alpha_{ir}|^2 + |\beta_{ir}|^2 = 1 \ (1 \le r \le R)$. α_{iR} and β_{iR} are defined as real numbers and $\alpha_{ir} \in [0,1]$ $\beta_{ir} \in [0,1]$ Therefore, $\alpha_{ir} = \sqrt{1-\beta_{ir}}$ .and Eq.(9) can be simplified as [10].

$$v_i = [\alpha_{i1} \quad \alpha_{i2} \quad \dots \quad \alpha_{iR}] = [v_{i1} \quad v_{i2} \quad \dots \quad v_{iR}] \tag{10}$$

The evolutionary process of quantum velocity (v_{ir}) is mainly completed through quantum rotation gate ($U(\theta_{ir}^t)$) that defined as $U(\theta_{ir}^t) = \begin{pmatrix} \cos\theta_{ir}^t & -\sin\theta_{ir}^t \\ \sin\theta_{ir}^t & \cos\theta_{ir}^t \end{pmatrix}$ .In QPSO algorithm, for simplicity of quantum rotation gate, the r-th quantum bit v_{ir} of the i-th quantum velocity is updated as

$$v_{ir}^{t+i} = \left| U(\theta_{ir}^t) v_{ir}^t \right| = \left(\begin{pmatrix} \cos\theta_{ir}^t & -\sin\theta_{ir}^t \\ \sin\theta_{ir}^t & \cos\theta_{ir}^t \end{pmatrix} v_{ir}^t \right) \tag{11}$$

Therefore, if use simplified quantum speed, Eq. (11) can be simplified as

$$v_{ir}^{t+1} = \left| v_{ir}^t \times \cos\theta_{ir}^{t+1} - \sqrt{1-\left(v_{ir}^t\right)^2} \times \sin\theta_{ir}^{t+1} \right| \tag{12}$$

If $\theta_{ir}^{t+1} = 0$, the v_{ir}^t is updated by the operator in a certain small probability which is described as

$$v_{ir}^{t+1} = \sqrt{1-\left(v_{ir}^t\right)^2} \tag{13}$$

Quantum particle swarm optimization is a multi-agent optimization system inspired by social behavior metaphor of agents. Each agent, called quantum particle, flies in a D-dimensional space according to the historical experiences of its own and its colleagues. There are h quantum particles that are in a space of D dimensions. The i-th quantum particle’s position in the space is $x_i = (x_{i1}, x_{i2}, \cdots, x_{iR}) (i = 1, 2, \cdots, h)$ which is a latent solution. The i-th particle’s quantum velocity is

$v_i=(v_{i1},v_{i2},\cdots,v_{iR})$.Until now, the best position (the local optimal position) of the i-th quantum particle is $p_i=(p_{i1},p_{i2},\cdots,p_{iR})(i=1,2,\cdots,h)$. $p_g=(p_{g1},p_{g2},\cdots,p_{gR})$ is the global optimal position discovered by the whole quantum particle swarm until now. At each generation, the i-th quantum particle is updated by the following quantum moving equations:

$$\begin{cases} v_{ir}^{t+1}=\begin{cases}\sqrt{1-\left(v_{ir}^{t}\right)^2}, \text{ if } p_{ir}^{t}=x_{ir}^{t}=p_{gr}^{t} \text{ and } \rho_{ir}^{t+1}<c_1 \\ \left|v_{ir}^{t}\times\cos\theta_{ir}^{t+1}-\sqrt{1-\left(v_{ir}^{t}\right)^2}\times\sin\theta_{ir}^{t+1}\right|, else\end{cases} \\ \theta_{ir}^{t+1}=e_1(p_{ir}^{t}-x_{ir}^{t})+e_2(p_{gr}^{t}-x_{ir}^{t}) \\ x_{ir}^{t+1}=\begin{cases}1, if & \rho_{ir}^{t+1}>\left(v_{ir}^{t}\right)^2 \\ 0, if & \rho_{ir}^{t+1}\le\left(v_{ir}^{t}\right)^2\end{cases}\end{cases} \quad (14)$$

ρ_{ir}^{t+1} is uniform random number and ω_{ir}^{t+1} is uniform random number which all between 0 and 1; $c_1\in[0,1/R]$ is mutation probability; $\left(v_{ir}^{t+1}\right)^2$ represents the selection probability that the quantum bit will be found in the "0" state. The values of e_1 and e_2 express the relative important degrees of p_i^t and p_g^t in the flying process.

4.2 The improved algorithm

The classical PSO[11-12] exist defects of local search precision is not high. Compared with PSO, the discrete QPSO has many advantages that include faster convergence speed, stronger search optimization ability and much fewer parameters. However QPSO is mainly used to solve the single objective optimization problem[13]. When using QPSO to solve the multi-objective optimization problem, the advantages of fast convergence speed easy to cause premature convergence. The algorithm will result in the loss of diversity of solution premature.

Mission planning issue is a discrete multi-objective optimization problem. In this section, in order to guarantee the diversity of solution, the non-dominated sorting and crowding distance which is proposed in the NSGA-II[14] is introduced into the discrete QPSO, so the proposed algorithm not only increases the diversity of the population, but also accelerates the convergence rate

4.2.1 Non-dominated sorting and crowding distance

The operation process of non-dominated sorting is as follow.

// fast non-dominated sorting (P)

for each individual $p\in P$

$S_p=\varnothing$; // A set of solutions that the solution dominates p dominate

$n_p=0$; // The number of solutions which dominate the solution p

for each individual $q\in P$

if ($p\prec q$) then // If p dominates q.

$S_p=S_p\cup\{q\}$; // Add q to S_p.

else if ($q\prec p$) then

$n_p=n_p+1$; //Increment n_p

if $n_p = 0$ then

$p_{rank} = 1$; //rank of individual p to 1.

$F_1 = F_1 \cup \{p\}$; // update the first front F1

$i = 1$;// initialize the front counter

while $F_i \neq \varnothing$ // while the i-th front is nonempty.

$Q \neq \varnothing$; // used for sorting the individuals for next front.

for each individual $p \in F_i$

for each $q \in S_p$

$n_q = n_q - 1$

If $n_q = 0$

Then $q_{rank} = i + 1$; //q belongs to the next front

$Q = Q \cup \{q\}$; // update the set Q.

$i = i + 1$;

$F_i = Q$; // Q is the next front.

In order to ensure uniformity of the solution, the crowding-distance computation is required. The calculation process of crowding distance can be described as follows.

// crowding-distance-assignment

$I = [I]$ // The number of individuals

for each i in I

$I[\mathrm{i}]_{distance} = 0$ // Initialize all crowded degree value to 0

for each objective m

$I = sort(I, m)$ //sort

$I[I]_{distance} = I[\mathrm{i}]_{distance} = \infty$//boundary individual crowded degree to infinite

for $i = 2\ to\ (\mathrm{I}\ \text{-}1)$

$I[i]_{distance} = i[i]_{distance} = (I[i+1]_m - I[i-1]_m)$//Calculate the crowded degree of each individual

4.2.2 The Flow Chart of Improved QPSO Algorithm

Flowchart of the MOQPSO algorithm is shown in Fig. 1.

5. Experimental results and analysis

Sample 1: Performance analysis of improved QPSO algorithm

Two benchmark functions are used to evaluate the performance of the improved QPSO. To evaluate the performance of the proposed QPSO, several performance metrics are evaluated. These metrics measure different aspects in multi-objective optimizations, including the follows[15].

(1) The distance between the computed Pareto front and the actual Pareto front of the Benchmark. This distance should be minimized and can be expressed by the generational distance (GD) shown as

$$\mathrm{GD}=\frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n} \tag{15}$$

Where n is the number of solutions in the non-dominated solution set and d_i is the Euclidean distance in the objective space between each solution and the nearest point in the actual front.

(2) The Spacing (SP) introduced by Eq.(9) is used to give a measure of the distribution spread in the non-dominated front.

$$\mathrm{SP}=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\bar{d}-d_i\right)^2} \tag{16}$$

Where $d_i=\min_j\left(\sum_{k=1}^{m}\left|f_k^i(x)-f_k^i(x)\right|\right)\ i,j=1,2,\cdots,n,\ \ j\neq i$ (17)

The formula refers to a non-dominated solution corresponding to the distance between the target vector and its closest to the target vector, $\bar{d}$ is the average of d_i. The value of SP is the same as that of GD, the smaller the better. If it is zero, the average of the non-dominated solutions of the algorithm is obtained.

Improved QPSO simulation parameters are set as follows: $e_1=0.1, e_2=0.05, c_1=1/60$. In this paper, we use the two functions of the Benchmark function to test.

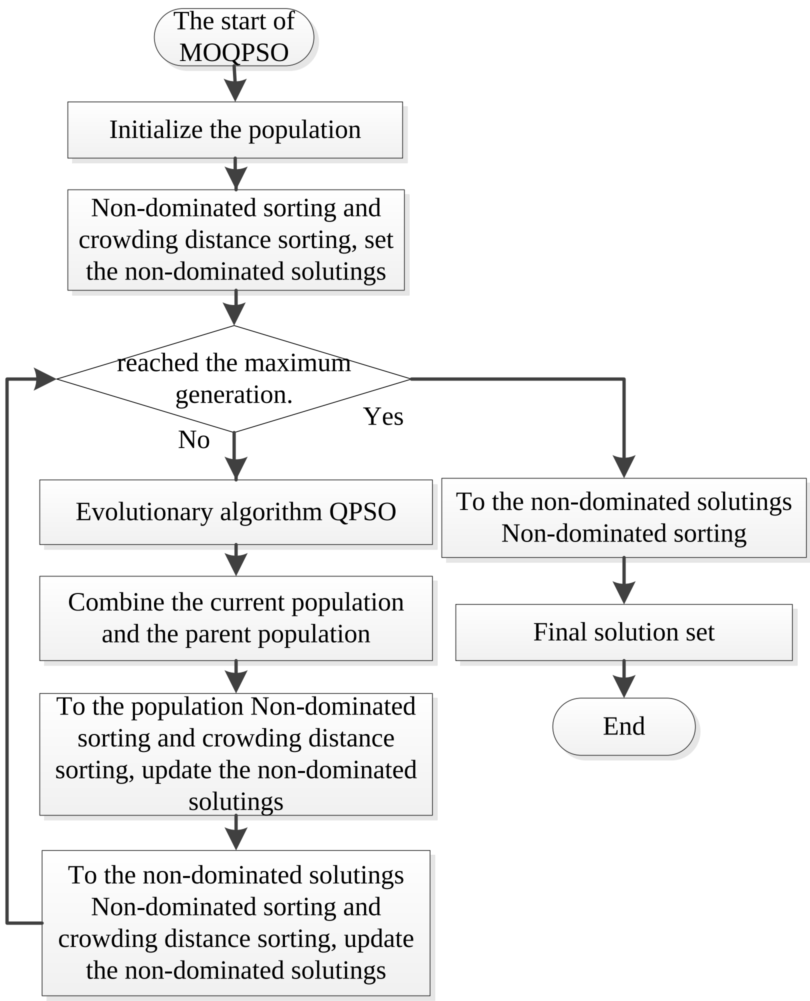

Fig 1. Flow chart of improved QPSO algorithm

Benchmark function 1:

$$\begin{cases} \min\ f_1(x) = 1 + (A_1 - B_1)^2 + (A_2 - B_2)^2 \\ \min\ f_2(x) = (x_1 + 3)^2 + (x_2 + 1)^2 \end{cases} \quad (18)$$

$$\begin{cases} A_1 = 0.5\sin 1 - 2\cos 1 + \sin 2 - 1.5\cos 2 \\ A_2 = 1.5\sin 1 - \cos 1 + 2\sin 2 - 0.5\cos 2 \\ B_1 = 0.5\sin x_1 - 2\cos x_1 + \sin x_2 - 1.5\cos x_2 \\ B_2 = 1.5\sin x_1 - \cos x_1 + 2\sin x_2 - 0.5\cos x \end{cases} \quad (19)$$

The comparison results between multi objective optimization algorithm based on particle swarm optimization algorithm is given in Table.1, and the optimal solution set of the improved QPSO algorithm is given in Fig.2.

Table 1. Comparison of test results

Algorithm	GD	SP
PSO[16]	0.00734	0.1438
Improved QPSO	0.00099	0.0379

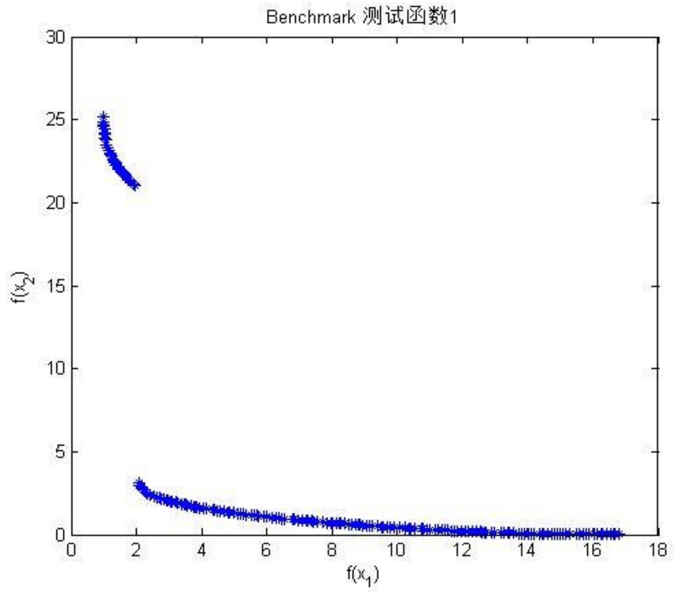

Fig.2 The optimization results of Benchmark function 1

Benchmark function 2:

$$\begin{cases} \min\ f_1(x) = (x_1^{\ 2} + x_2^{\ 2})^{\frac{1}{8}} \\ \min\ f_2(x) = ((x_1 - 0.5)^2 + (x_2 - 0.5)^2)^{\frac{1}{4}} \end{cases} \quad (20)$$

It is obvious that the metric GD and metric SP are smaller, and GD=3.3143*10-4, SP= 0.0032. The optimal solution set of the improved QPSO algorithm is given in Fig.3.

In summary, improved QPSO algorithm performance is better than multi-objective PSO to solve the discrete multi-objective optimization problems. Simulation experiment and result analysis are carried out to verify the feasibility of the improved QPSO algorithm in the multi objective on orbit servicing spacecraft mission planning problem.

Sample 2: Simulation example of spacecraft mission planning problem based on improved QPSO

In order to demonstrate feasibility of improved QPSO algorithm, several experiments were carried out. For this purpose, a MATLAB computer simulation program was developed. Assume that there are two service spacecraft (SS) with different service capability on the same orbit, waiting for service order to serve the target spacecraft (TS). Also there are 4 target spacecraft on different orbits, the requirement is service spacecraft finish on-orbit service for target spacecraft in the limited time period and get the best result. Optimal configuration of sample 1 and sample 2 are set as follows.

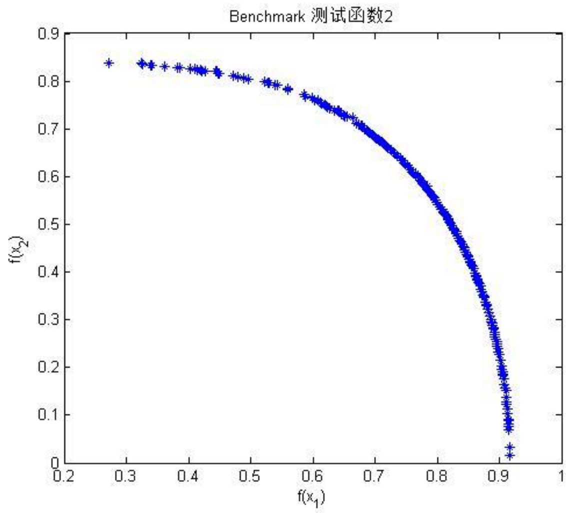

Fig.3 The optimization results of Benchmark function 2

Table 2. Configuration of multi-objective optimization

Parameter	Quantity	Value	Unit
D	Number of Decision variables	12	
T	Maximum time	7000	s
t_0	Initial time	100	s
Δv_{max}	Maximum velocity increment	3	Km/s
Δt_{min}	Minimum time interval	100	s

In the following simulations, binary-encoding is used, and the length of every variable is 30 bits. Simulation parameters are set as: e1=0.5, e2=0.3, c1=1/D, Maximum generation is set as 100.

Table 3. Initial orbital parameters of the spacecraft [17]

Spacecraft	a/(m)	e	i/(°)	Ω/(°)	ω(°)	f/(°)	Priority
SS1	7150000	0.01	98	220	30	230	
SS2	7150000	0.01	98	220	30	50	
TS1	7300000	0.02	103	220	0	130	0.7
TS2	7250000	0.02	104	222	25	230	0.9
TS3	7300000	0.01	95	215	20	50	0.6
TS4	7250000	0.03	94	218	10	15	0.7

Note: We set the same initial parameters as in reference [17] to compare the two results.

In order to analyze the effect of multi-objective optimization, set the initial parameters of the spacecraft's orbit, refer to Table 3 as Reference [17].

We choose three groups of Pareto optimal solution calculated by Improved QPSO, and compare the result calculated by Divided Weighting Method (DWM) method under the same configuration. The comparative results are given in Table.4.

Table 4. Comparison between simulation results

Algorithm	Optimal Assignment solution	Priority Level	Fuel Consumption/(m/s)
DWM	SS1→TS2 SS2→TS1	1.6	2183.4
Improved QPSO	SS1→TS2 SS2→TS4	1.6	1599.1
	SS1→TS2 SS2→TS3	1.5	1807.3

6. Conclusion

The on-orbit servicing mission assignment is very important to improve the cooperative work ratio of the on-orbit servicing spacecraft. One mission of on-orbit servicing can be fulfilled in many ways and proper mission assignment must be guaranteed. Based on the characteristics and technical specifications of the mission planning issues, a multi-objective quantum-behaved particle swarm optimization based on QPSO and non-dominated sorting is proposed. Since improved QPSO has the characteristic of both QPSO, which has fast convergence rate and accurate convergence value and non-dominated sorting, used to obtain non-dominated solutions, it is used to solve spacecraft task allocation. By analyzing the critical index factors which contain target spacecraft value, task completion time and distance consumption, an on-orbit spacecraft task allocation model is formulated. The best plan was achieved by Pareto optimal sets and ideal solution can be chose as necessary. Finally the example of simulation was given, it compared with another algorithm. Simulation results show that the improved QPSO has fast convergence and better distribution.

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