A New Approach on Satellite Mission Planning with Revisiting Requirements

Yuyan Liu[1], Yuqing Li[1](✉), Pengpeng Liu[2], Xiaoen Feng[1], Feilong Jiang[1], and Mingjia Lei[1]

[1] Harbin Institute of Technology, Harbin 150001, China
bradley@hit.edu.cn
[2] Naval Research Academy, Beijing 10061, China

Abstract. With the development of space science and technology, the demand of observation mission increases. However, due to the limitations of the performance of platform or payloads and space environment of the remote sensing satellite, the observation ability is restricted, so it is necessary to carry out the mission planning. Aiming at the observation task of revisiting hot spots by remote sensing satellite, this paper firstly analyzes the practical constraints, and designs several functions about optimization targets. Secondly, the mathematical model was established. Thirdly, the algorithm to solve the problem was based on PBIL. Finally, to examine the performance of the algorithm, this paper creates simulation scenarios and test cases by means of STK, and obtains the initial simulation time window sequence. By comparing with the results of genetic algorithm, the effectiveness of the algorithm in solving the problem of multi-satellite revisit mission planning has been verified, which is better than the results of genetic algorithm.

Keywords: Satellite mission planning · Revisiting requirements · Population based incremental learning algorithm · Genetic algorithm

1 Introduction

Satellite mission planning is to generate a planning sequence for observation missions that satisfies various constraints based on limited resources. In addition, there is a need for repeated observation in hot spots to obtain effective local information. At the same time, the cost of satellites is relatively high, so the overall planning of limited satellite resources in order to achieve better mission requirements under certain resource conditions has become an urgent problem. Scholars from various countries have studied this problem from multiple perspectives.

This study was supported by the Key Laboratory Opening Funding of Harbin Institute of Technology of Deep Space Exploration Landing and Return Control Technology (HIT.KLOF. 2018.076, HIT.KLOF. 2018.074), and the pre-research projects of equipment development department of China Central Military Commission (JZX7Y20190243001201).

Q. Wu et al. (Eds.): WiSATS 2020, LNICST 358, pp. 198–209, 2021.
https://doi.org/10.1007/978-3-030-69072-4_17

Deng bao song and others summarized the current status and future trend of mission planning. They mentioned that satellite mission planning is a NP hard problem in theory. In the research and practice process, it is usually necessary to establish an effective constraint model based on specific tasks, in order to ensure the feasibility and reliability [1]. Scholars have made extensive studies on task planning from different perspectives, including overall problem analysis, algorithm implementation, software implementation, and analysis of different constraints. In the paper of Fatos Xhata et al., the genetic algorithm of STK is used to carry out multi-objective task scheduling [2]. There are also many ways to use intelligent algorithms to solve satellite mission planning problems. For example, in the paper written by Zhang Zhengqiang et al., neighborhood search algorithm was used. After the reasonable allocation of the target area, they comprehensively designed greedy random variable neighborhood search algorithm [3]. Song Yanjie proposed an improved genetic algorithm that could freely switch between global optimization and local optimization according to the population situation. In addition, he also proposed a task planning algorithm that could select a reasonable execution time for the improved mission sequence [4]. Hu Xiaoxuan et al. invented the method and system of multi-star emergency mission planning based on pointer neural network [5]. In many scholars' articles, it is often considered to improve the algorithm [4, 8] or combine the two algorithms [6] to solve the problem.

Based on the above analysis, the solving ability of the existing methods needs to be further improved, and the revisiting demand of hot spots is not fully considered. Therefore, based on previous studies and taking small satellites as the research object, this paper designed a population incremental learning algorithm to solve the problem of revisit mission requirements, and compared the results with the genetic algorithm, conducted simulation experiments on the multi-star time window sequence to verify the effectiveness of the algorithm.

2 Description of the Problem

2.1 Problem Overview and I/O

During the observation mission, the satellite carries a sensor as a payload to observe the earth and collect information, and then sends them down to the ground station. In the case of multi-satellite operation, the observation task is determined, the resource utilization rate is improved, and the observation effect is optimized.

The basic input elements of the question usually include the following aspects:

(1) satellite orbit parameters: the satellite's orbit is generally described by the orbit parameters (orbital altitude, orbital inclination, right ascension of ascending node and initial latitude argument);
(2) payload parameters: since the main problem in this paper is to use intelligent algorithm for revisiting mission planning, synthetic aperture radar (SAR) sensors that can work in the shadow area are selected uniformly to achieve the optimal value of observation efficiency. The power of the sensor and the field of view Angle;

(3) satellite platform parameters: power supply capacity, storage space capacity, data transmission time window, time for the satellite to enter the shadow area and light area, and angular velocity of the satellite's pitch axis and roll axis. At the same time, the satellite has the ability to swing and maneuver, which can improve the observation effect to some extent.
(4) Target: This paper selects the northern Indian Ocean region as an example. For remote sensing satellites, observation targets can be point targets or regional targets. In the subsequent revisiting mission planning, point targets are selected for specific analysis.

The basic output elements of the problem usually include the following two aspects: the first is the mission planning scheme, which can be represented by a structure, including the satellite number of the corresponding mission, the number of the ground target, the starting and ending time of the observation time window, and whether the window is selected or not. The second is the expression of observation effect, which mainly includes observation times, total observation time, mean revisiting time and mean variance of revisiting time.

2.2 Constraint Conditions and Optimization Objectives

The constraint conditions of the problem mainly include: time window conflict (A satellite can only observe one target at a time; In order to improve resource utilization, the same target can only be observed by one satellite at the same time), power constraints (satellite battery charging activities must be carried out when the circle of light period and meet the lap balance and depth of discharge shall not exceed 20%), storage and sufficient attitude adjustment time for observations.

Optimization objectives of the problem include: the satellite should ensure 100% coverage or observation of ground targets; Total observation times, total observation time, mean revisiting time and mean variance of revisiting time of the satellite to the ground target. Among them, the total number of observations and the total observation time are the primary objectives. In the optimization of the time window sequence, these two objectives are firstly optimized, and the average revisiting time and the variance of revisiting time are the secondary objectives. Based on the achievement of the first two objectives and then according to the secondary goals to optimize or take them as indicators to judge the quality of the results.

2.3 Simulation Constellation and Obtain

By analyzing and discussing the influence of orbit parameters (orbital altitude, orbital inclination, right ascension of ascending node and initial latitude argument) on the regional coverage, the constellation is finally determined. Considering the characteristics of small satellites, low-earth orbit is chosen for mission orbit, in the other word, the orbital altitude is less than 1000 km, so that the satellite has better observation results of the selected region. At the same time, the circular orbit is used for analysis, because the circular orbit has a uniform resolution for the ground target compared with the elliptical orbit. The target area is located in the North Indian Ocean area. The specific latitude and longitude were set as [0°N-20°N,58°E-70°E], the regional target resolution was set as 0.5°, the simulation time was set as 4 days, the sensor's field of view Angle was set as 25°, and the satellite adopted a two-body model. After experimental simulation and analysis, the specific parameters of the four satellites were finally selected as shown in the following table (Table 1):

Table 1. Simulation satellite parameters

Satellite number	Orbital altitude (km)	Orbital inclination (deg)	Ascending intersection right ascension (deg)	Initial latitude argument (deg)
1	600	20	0	360
2	600	20	90	330
3	600	20	180	120
4	600	20	270	180

Thirteen hotspots were selected in this region, and through STK analysis of visibility I finally obtained the initial sequence of 221 time Windows.

3 Design of Algorithms

3.1 Population Based Incremental Learning Algorithm

Incremental learning refers to a system that constantly learns new content from the outside world and updates the content learned. And population based incremental learning is based on a population, and regards the evolution of a population as a learning and updating process, and uses the acquired knowledge to guide the generation of the next generation of population, thereby producing a better solution of the fitness value results.

In the process of code design, it is possible to model the optimization process of population in genetic algorithm for processing and analysis. The main algorithm steps are as follows:

(1) chromosome coding

The sequences obtained in the previous chapter are first sorted by the initial time of the time window, then sorted by the satellite number, then according to whether the satellite time window is selected (1 means selected, 0 means not)to number them.Suppose there are 100 individuals in a population, and the initial sequence has n time Windows. Therefore, the chromosome pool matrix (Cmepool) is illustrated as follows:

$$Cmepool = \begin{bmatrix} 1101 & \nu & 1010 \\ \vdots & \ddots & \vdots \\ 1001 & \nu & 1110 \end{bmatrix}_{100*n} \quad (1)$$

(2) generation initial population

When using the genetic algorithm to calculate, it is necessary to first generate an initial population for subsequent optimization selection. A random pool matrix containing only 0 or 1 is directly generated by the random function, which is the initial population.

(3) fitness evaluation function

Before the fitness evaluation, eliminating the conflicts first. The conflict includes: satellite time window conflict, ground station time window conflict, attitude adjustment time conflict, energy constraint conflict and storage constraint conflict. If there is a conflict, the relevant time window will be removed randomly and then check conflict constraint again.

The fitness calculation function adopts two schemes. The first is to use the total observation time as the output variable to be optimized, that is, to traverse all the selected time windows and calculate the total observation time as corresponding chromosome's fitness value. The second is to take the total number of observations as the output variable to be optimized, that is, to traverse all the selected time windows and calculate the number of observations as corresponding chromosome's fitness value.

(4) population learning process

The population learning process is inseparable from the design of the learning process. The initial learning probability matrix is set as following formula.

$$p_1 = 0.5 * ones(1, 221) \tag{2}$$

Where ones() is a function of MATLAB that can generate all 1 matrix.

Then the population will improve the learning probability matrix according to a certain learning rate (α).

$$p_2 = (1 - \alpha)p_1 + \alpha p_{new} \tag{3}$$

Where p_{new} is a chromosomal gene with better fitness in the previous generation population.

Then design a mutation function for the learning probability matrix to increase the diversity of the population and avoid falling into a local optimal solution. The mutation probability is 0.1 and the mutation size is 0.2. The mutation formula is as follows:

$$p = p_2 * (1 - 0.2) + randi([01], 1) * 0.2 \tag{4}$$

Where randi() is a built-in pseudo-random integer function generated by MATLAB.

According to this learning probability, the next generation of population is generated.

Realizing the Algorithm

MATLAB programming is adopted to realize the algorithm. The main steps are designed according to the previous section, and the flow chart is as follows (Fig. 1):

Since the learning rate has a great influence on the evolution of the algorithm, analyzing the impact of the learning rate on the simulation, finally the learning rate is selected as 0.75 in this paper.

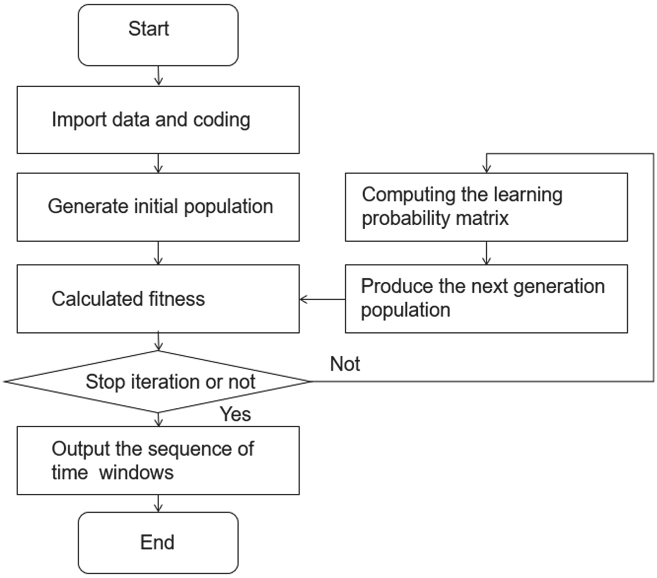

Fig. 1. Flow chart of population incremental learning algorithm.

3.2 Genetic Algorithm

The difference between genetic algorithm and population incremental learning algorithm design is how to generate the next generation. The population based incremental learning algorithm is based on a well-adapted individual performing directed learning to generate the next generation. And genetic algorithm generate the next generation through the selection operator (according to the proportion of the probability which is proportional to the individual fitness, operator determines whether the individual into the mating pool and it also adopts elite reserved strategy), the crossover operator (random selection of two individuals for single-point crossover to obtain offspring, Choose the best two of the four individuals) and mutation operator (with the possibility to carry out mutations of some chromosomal genes to increase the diversity of individuals) to produce (Fig. 2).

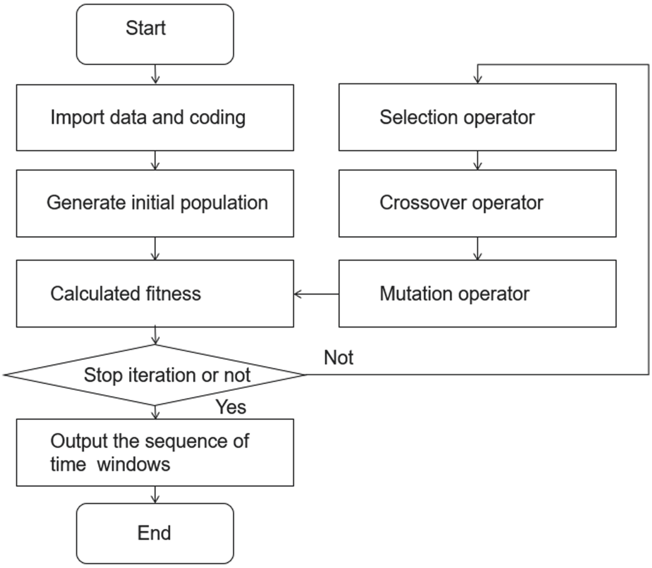

Fig. 2. Flow chart of genetic algorithm.

4 Examples and Analysis

4.1 PBIL Algorithm Simulation Examples

The learning rate (α) is 0.75, the number of iterations was 100, and the population size was 100, the mutation probability and the size of the mutation value were selected as shown in formula (4) above. The fitness is calculated according to the total observation time (example1) and observation times (example 2), and the fitness results were shown as follows (Fig. 5):

In the calculation result based on the total observation time as the fitness, the optimal solution is individual 1. In this last generation, the individual 3 has the lowest average revisiting time and individual 4 has the lowest mean variance of revisiting time. And in the result calculated according to the total observation time as the fitness, the optimal solution is individual 2, in the last generation, individual 5 has the least average revisiting time and individual 6 has the lowest mean variance of revisiting time.

It can be seen from Fig. 3 and Fig. 4 that it is feasible to apply PBIL to the satellite mission planning problem, and it can achieve convergence within a certain iteration range with a good convergence result. In the initial iterations, population's fitness rose rapidly, due to the huge role of directional learning which can make the whole population evolution towards the direction of the optimal fitness. While the later iteration process mainly relies on the effect of mutation to pull the population's fitness, and the upward space of the fitness decreases, so compared to the initial iterations the evolution process is relatively slow. The highest and lowest fitness of each generation are rising in fluctuation, because there is a certain probability of producing genes inconsistent with the overall learning direction. Such mutant genes can not only increase the population diversity to a certain extent, but also lead to the fluctuation of individual fitness in the population.

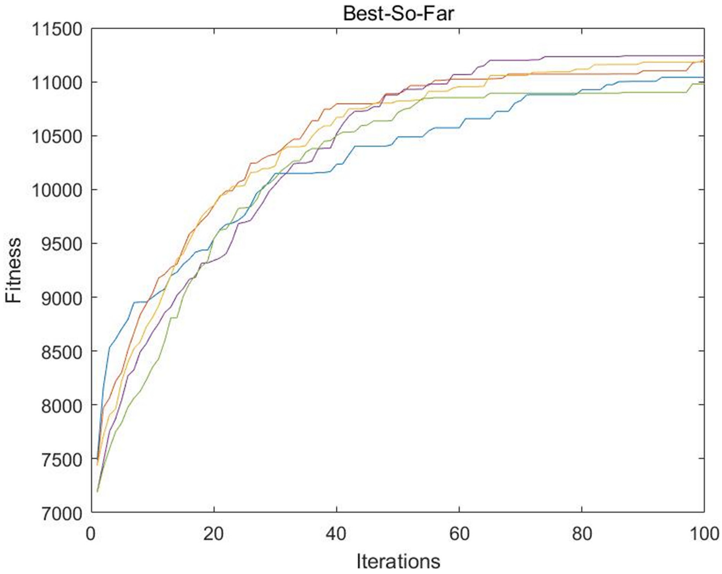

Fig. 3. Example 1

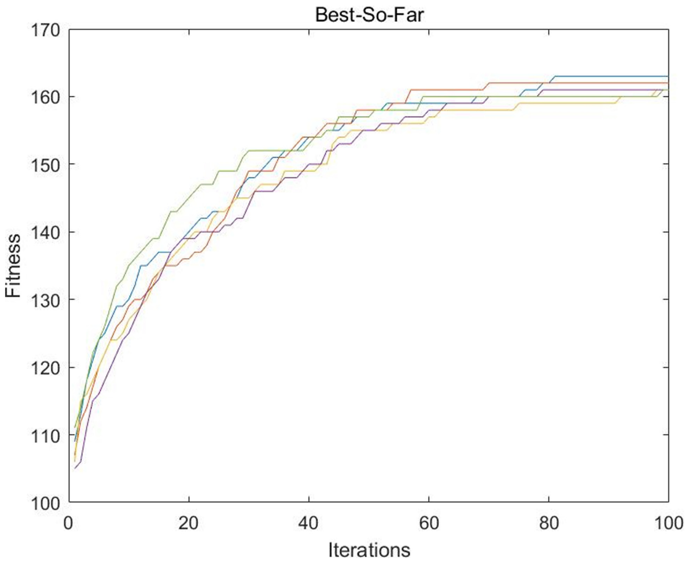

Fig. 4. Example 2

According to the previous section, the six individuals' data of the PBIL algorithm are as follows:

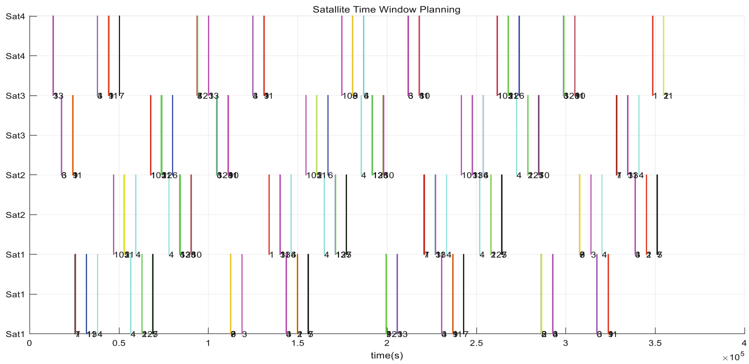

Fig. 5. Time window planning diagram of PBIL individual 1 satellite

4.2 Genetic Algorithm Simulation Examples

A task planning program based on genetic algorithm was designed by MATLAB. The termination condition was the number of iterations, the population size was 100, the number of iterations was set to 100, the crossover probability was 1, and the mutation probability was 0.1. The fitness function was calculated according to the total observation time (example 3) and the total observation times (example 4). And the simulation results are shown in the following figure (Figs. 6 and 7):

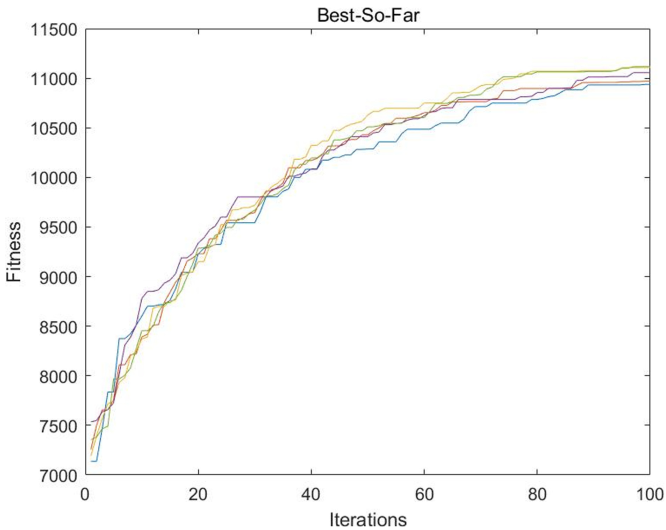

Fig. 6. Example 3

It can be seen from the above figures that the use of genetic algorithm can also achieve convergence with a good convergence value.

According to the previous section, the six individuals' data of the genetic algorithm are as follows:

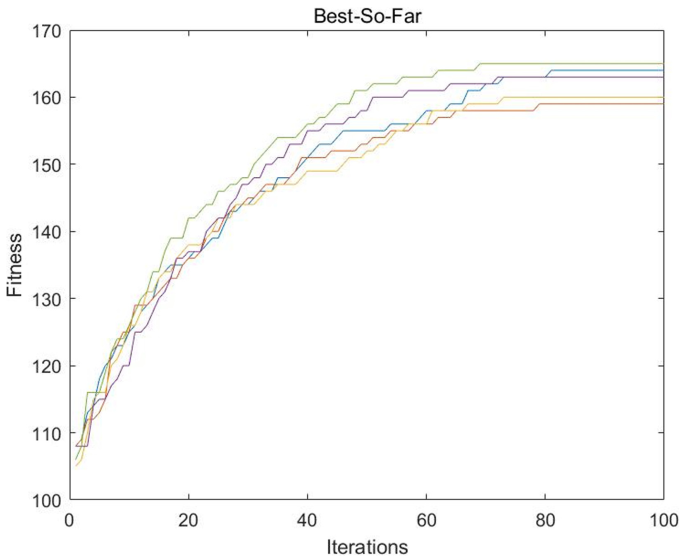

Fig. 7. Example 4

4.3 Comparison and Analysis

Convergent Value

Comparing PBIL and GA individuals in Table 2 and Table 3, the result of the two algorithms has little difference. This shows that both algorithms can achieve the desired convergence results as long as there are enough iterations.

Table 2. The simulation results of PBIL.

Individual code	Total number of observations (times)	Total observation time (10^4 s)	Average revisiting time (10^4 s)	Mean variance of revisit time (10^4 s)	CPU computation time (s)
P1-1	162	1.2141	2.4513	2.0641	560.7
P1-2	157	1.0744	2.4150	2.0575	561.0
P1-3	160	1.0980	2.4331	2.0305	560.9
P2-1	163	1.0744	2.4475	2.0996	576.5
P2-2	161	1.0613	2.4464	2.0984	576.7
P2-3	160	1.0527	2.4468	2.0953	576.8

Iteration Times of the Same Fitness

By comparing the number of iterations corresponding to the same fitness in the four graphs, the genetic algorithm has more iterations than the population based incremental

Table 3. The simulation results of GA.

Individual code	Total number of observations (times)	Total observation time (10^4 s)	Average revisiting time (10^4 s)	Mean variance of revisit time (10^4 s)	CPU computation time (s)
G1-1	157	1.1117	2.4913	1.9845	1442.3
G1-2	155	1.0899	2.4851	1.9852	1442.6
G1-3	154	1.0877	2.4854	1.9688	1442.6
G2-1	164	1.0924	2.4596	1.9537	1794.5
G2-2	163	1.0852	2.3870	1.9730	1794.8
G2-3	163	1.0874	2.4485	1.9116	1794.7

learning algorithm in the initial stage. In addition, the difference between the highest and lowest values of each generation in PBIL algorithm is smaller than that in GA algorithm.

Because the population generation of PBIL algorithm is based on a specific learning probability with strong orientation, which can make the individuals in the whole population iterate in a clear optimization direction. While the genetic algorithm needs to drive the population to change optimally through two ways: elite retention strategy and choosing two excellent ones from parents and two children. So, the orientation is relatively weak.

CPU Computing Time
Comparing PBIL and GA individuals 1 and 2 in Table 2 and Table 3, it is obvious that the genetic algorithm takes more than twice as long as the computing time of PBIL. This is because the genetic algorithm needs to pass three steps including selection, crossover, and mutation, when generating the next generation. What's more in the process of crossover the fitness function is called to increase the calculation time. While the population based incremental learning algorithm only needs to determine a learning probability matrix to generate the next generation.

All in all, the population incremental learning algorithm is superior to the genetic algorithm in terms of number of iterations required, and CPU computing time.

5 Conclusion

Aiming at the problem of multi-satellite remote sensing mission planning, reasonable modeling was carried out after analyzing its input and output and constraints and optimization objective. This paper used the population incremental learning algorithm and genetic algorithm to optimize the time window series. Taking 4 small satellites to observe 13 regional hotspots as an example Simulation. The calculation examples show that it is reasonable and effective to use this method to solve similar problems. It also shows that the performance of the population incremental learning algorithm is superior to the genetic algorithm.

It should be pointed out that this paper only achieved research results in a certain aspect, and the research on observation constraints is not sufficient. Other more complex constraints will be further considered in the future, and the algorithm will be further optimized for the actual application.

References

1. Baosong, D., Zhipeng, M., Yi Yujiang, Yu., Ye, Z.X.: Research on mission planning of earth observation satellite. Comput. Measur. Control **27**(11), 130–139 (2019)
2. Xhafa, F., Sun, J., Barolli, A., Biberaj, A., Barlli, L.: Genetic algorithms for satellite scheduling problems. Mob. Inf. Syst. **8**(4) (2012)
3. Zhang, Z., Guo, J., Ruan, Q.: Remote sensing satellite mission planning algorithm for regional target. Radio Eng. **39**(09), 40–43 (2009)
4. Song, Y., Wang, P., Zhang, Z., Xing, L., Chen, Y.: Improved genetic algorithm for multi-star task planning. Control Theory Appl. **36**(09), 1391–1397 (2019)
5. Hu, X., et al.: Method and system of multi-star emergency mission planning based on the needle neural network. CN110599065A, 20 December 2019
6. Zheng, Z., Guo, L., Gill, E.: swarm satellite mission scheduling & planning using hybrid dynamic genetic algorithm. Acta Astronaut. **137**, 243–253 (2017)
7. Wu, G., Liu, J., Ma, M., Qiu, D.: A two - phase scheduling method with the consideration of task clustering for earth observing satellites. Comput. Oper. Res. **40**(7) (2013)
8. Li, Y., Wang, R., Xu, M., Cui, H., Wang, H., Xu, R.: Research on a class of multi-resource measurement and control scheduling problem based on improved genetic algorithm. J. Aerosp. **33**(01), 85–90 (2012)
9. Zhang, Q.: An improved incremental learning algorithm based on group. In: Technical Committee on Control Theory, Chinese Association of Automation. Proceedings of the 26th China Control conference. Technical Committee on Cotrol Theory, Chinese Association of Automation, Professional Committee of Control Theory of China Automation Society, pp. 3273–3276 (2007)