Multi-objective mission planning problem of agile Earth observing satellites

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Abstract: In this paper, we concern multi-objective mission planning problem of a constellation of the next generation agile Earth-observing satellites. As usual, the goal of Earth-observing satellite mission planning is to maximize the sum weights of selected tasks. But for agile satellites, based on its stronger ability, single criterion is often a poor measure of planning results. For agile satellite, the starting times of the observations are free, different starting time to observe brings different image quality. Meanwhile, for a constellation of satellites, some of them are used frequently and the others are used scarcely may be bad way of usage. The good planning solution is to arrange the satellites reasonably to take images as many as possible with good quality and satisfy different users. We give four criteria to evaluate scheduling results: the sum of weights, average image quality, balance usage of satellites and selected task numbers. A multi-objective evolutionary algorithm is designed to solve the problem. Experimental results suggest that multi-objective mission planning produce good quality of planning result and our algorithm works well for the multi-objective mission planning problem of agile satellites.

I. Introduction

The mission of Earth observing satellite (EOS) is to acquire photographs of specified areas on Earth surface at the requests of users. The goal is to select a feasible task sequence to maximize the sum of weights. The new generation EOS with three degrees of freedom, such as the American Ikonos satellite and the French Pleiades ones, is called Agile EOS (AEOS). All instruments are fixed on the satellite, and the whole satellite can move on the three axes (yaw, roll and pitch). These new capabilities of satellite provide new advantages for observation. The observing time windows are much longer, and the number of ways of observing target area on the Earth surface may be infinite, since starting times of the observation are free. As a result, agile satellite can observe much more tasks than non-agile satellite, see figure 1. Besides, the area task containing multiple strips may be observed for one pass, which can greatly shorten the complete time of the task. Obviously, these advantages bring much more difficulties to the selection and scheduling of AEOS observations since the search space is considerably larger. For agile satellite, since the starting times of the observations are free, different starting time to observe a task would bring different image quality. Meanwhile, the customers care about the event of taking image and the image quality, but the manager of satellites may care about the reliability more. For a constellation of satellites, different satellites can see different targets, and this may result in that some of them are used frequently and the others are used scarcely. The good planning solution is to arrange the satellites reasonably to take images as many as possible with good planning quality. The objective function of EOS mission planning is often the sum weight or priority of tasks in schedule, but for agile satellite, based on its stronger ability of observation, single objective function will be a poor measure of planning results. We give other three criteria to measure the planning results. These criteria are as follows:

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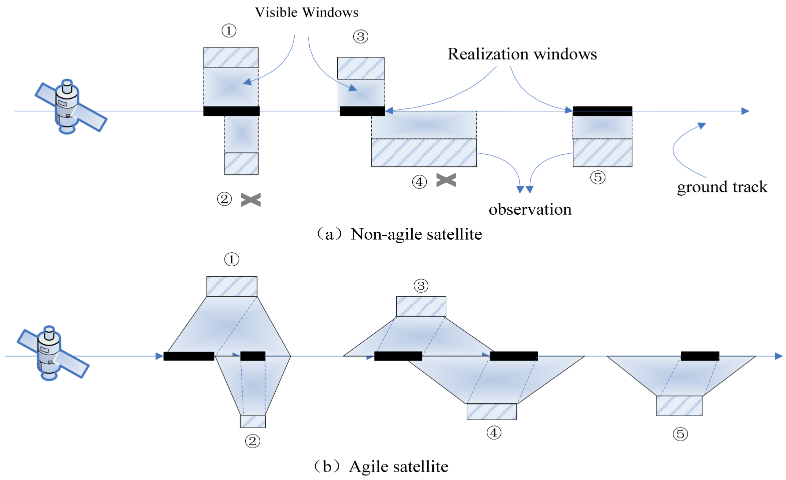


Figure 1. Non-agile satellite VS Agile Satellite – a picture taken from reference [1]

A. Image Quality

When camera parameter and target ground character are fixed, the image quality depends on the distance between satellite camera and the target. The distance is in direct proportion to the observing angle of satellite, see figure2. Different observing angles bring different image qualities. For most of the image users, the higher image quality, the better.

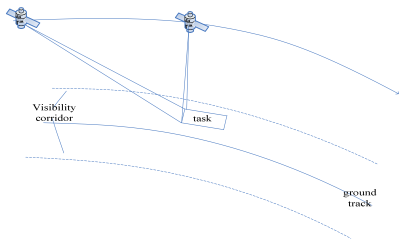


Figure 2. Different angles to observing target

B. The Usage of Satellite

The customers care about whether the image is taken and the image quality, but the manager of satellites may care about the reliability more. The good planning solution is to take images as many as possible with good quality. Meanwhile, satellites are well balanced. See figure 3, all of the four targets can be observed by the two satellites; if only consider profit for scheduling, satellite one may observe four targets and satellite two will do nothing. For a constellation of satellites, targets can be seen by different satellites. If one of them is always busy and the other is always free that may be bad usage of satellites.

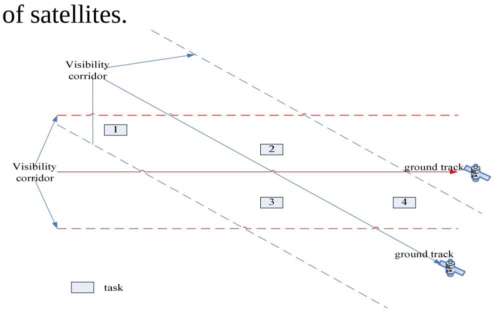


Figure 3. Balance use of satellite

C. The Total Numbers of Tasks in the Schedule

In the EOS domain, it is often expressed that the more users involved the better, even if they are not fully satisfied (e.g., less data). This would keep the lower priority tasks "alive", while the higher priority tasks would still get more preferences satisfied. Meanwhile, the priority of tasks is subjective and may not reflect the really think of users. More users requests are scheduled may satisfy more users, the result may be a good solution.

We can see that, if we do not consider the criteria above, the planning result will be lower quality and will not exert the ability of agile satellite and may not satisfy the users. By the way, in application, different users can also choose some of the criteria to get their planning result based on their preference. AEOS mission planning problem of single object is already a NP hard problem[2], and multi-objective planning is much more difficult.

The remainder of the paper is organized as follows. Section II gives the previous work in EOS domain. Section III presents a detailed description of the scheduling model. Section IV develops a multi-objective evolutionary algorithm to solve the problem. Section V gives experimental results to test our model and algorithm. Finally, we will state our conclusions and present directions for future work.

II. Previous Work in EOS Domain

Wolfe and Sorensen[3] gave an overview of the EOS scheduling problem and introduced their models. They considered three approaches to solve the EOS scheduling problem: a priority dispatch method, a look-ahead algorithm and a genetic algorithm. A fast and simple priority dispatch method was designed to produce acceptable schedules most of the time. The look-ahead algorithm extends the priority dispatch method by redefining the best location rule to looking ahead in the queue of unscheduled requests. The genetic algorithm is slower but can create near-optimal results. The genetic algorithm operates on a permutation-based representation which is easier to perform genetic mutation and crossover operations.

Globus[4] and his group at NASA Ames characterized the EOS scheduling problem by multiple complex constraints and large search spaces. The optimization object is to observe as many high priority requests as possible. They compared multiple variants of the genetic algorithm, hill climbing, simulated annealing, squeaky wheel optimization and iterated sampling on ten realistically sized model EOS scheduling problems. Their study suggests that the simulated annealing performs the best under their scenarios.

Lemaitre and Verfaillie[2] provided a comprehensive description of AEOS scheduling problem. They analyzed the difficulties of the problem and given the overall problem. Then they simplified the problem to the AEOS Track Selection and Scheduling Problem and proposed four different methods to solve the simpler problem: a fast greedy algorithm, a dynamic programming algorithm, a constraint programming approach, and a local search method.

Bistra Dilkina and Bill Havens[5] proposed a synthesis of permutation-based search and constraint propagation for AEOS scheduling in order to incorporate the advantages of both techniques. Large neighborhood behavior of permutation search was obtained for oversubscribed resource scheduling problems. Coupled with constraint propagation over image acquisition time windows, they investigated three different local optimization algorithms (hill-climbing, simulated annealing and squeaky wheel optimization). Uniform random image targets and actual urban image target sets were considered into experiments. New image requests are dynamically added to the problem to measure the schedule quality and solution degradation. Their results suggest that permutation-based search coupled with constraint propagation works very well for agile EOS scheduling.

A tabu search algorithm was given to solve the AEOS scheduling problem in [6]. The tabu search algorithm explores a search space by consistent and saturated configurations. The consistency of each new move in the search procedure is ensured by effective constraint propagation. Moreover, their algorithm is also is bridged with systematic search which uses partial enumerations. In order to obtain better solution, they introduced a secondary problem: minimization of the sum of the transition durations in a schedule. A dynamic programming algorithm was given to calculated upper bounds on a relaxed problem.

Reference [7] proposed a chronological forward search planning algorithm for a constellation agile Earth observation satellites. The constellation they consider is made up of two identical satellites moving on the same orbit with a phase shift of 180 degrees between the two satellites. The planning algorithm covers all satellite activities and meets all the physical constraints of their satellites. It also contains decision heuristics, constraint checking, limited look ahead, and backtrack in case of constraint violation. They also showed that how the planning algorithm can be used in this replanning setting, with some modifications that limit computing time and favour plan stability and optimality.

Reference [8] presented their study about autonomous decision making on board for AEOS equipped with a cloud detection instrument. They described the online decision-making problem to manage on board, provided a reactive/deliberative architecture, and an iterated stochastic greedy search algorithm is given in the deliberative part.

Bianchessi [9] presented a tabu search heuristic for the multi-satellite, multi-orbit and multi-user management of Earth observation satellites problem, under operational constraints. An upper bounding procedure based on column generation is used to evaluate the quality of the solutions.

We notice that the objective function of almost all papers concerning about EOS or AEOS scheduling problem is single, usually the sum of weight or the number of complete tasks. Only reference [3] pointed that single objective function in EOS mission planning, is often a poor measure of quality because it does not take into account all of the possible criteria, they suggested weighted average method to solve the multi-objective mission planning problem.

III. Problem Modeling

A. Mathematical Statement

Let $T = \{t_1, t_2, \ldots, t_{N_T}\}$ be the set of tasks, and N_T be the number of tasks.

Let $S = \{s_1, s_2, \ldots, s_{N_S}\}$ be the set of satellites, and N_S be the number of satellites.

Let O be the set of strips, $O_i = \bigcup_{j=1}^{N_S}\bigcup_{k=1}^{N_{ij}}\bigcup_{v=1}^{N_{ijk}} o_{ijkv}$ be the strips of task t_i, N_{ij} be the observing opportunities of satellite s_j to task t_i, N_{ijk} be the strips number of task t_i in number k opportunity of satellite s_j; let P_i be the set of strips of task t of opportunity i, $P_i \in O$.

o_{ijkv} be number v strip of task t_i in number k opportunity of satellite s_j.

Each strip o_{ijkv}, is associated with a time window [a_i, b_i], an observing duration d_i, a weight w_i, a roll angle $roll_i$, and a pitch angle $pitch_i$; All strips of task t_i have the same weight.

Let [$SceS, SceE$] be the start time and end time of plan;

Let TS_{ij}, $i, j \in O$ be the attitude maneuver time between strip i and j. Let $f_{ij} \in (0,1)$, be 1 if strip i is followed by strip j in the selected sequence;

Let st_i be the observing start time of strip i.

B. Decision variables

Let $x_{ijk} = 1$, if task t_i is selected in number k opportunity of satellite s_j, and 0 otherwise.

Let $x_{ijkv} = 1$, if strip o_{ijkv} is selected in number k opportunity of satellite s_j, and 0 otherwise.

C. Objective Functions

The objective functions to be minimized are

- Profit: minimize the total profit of unselect tasks

$$Profit = \min\left(\sum_{i=1}^{N_T} w_i - \sum_{i=1}^{N_T}\sum_{j=1}^{N_S}\sum_{k=1}^{N_{ij}} x_{ijk} * w_i\right)$$

- Image Quality: minimize the observing angles of selected task strips

The average pitch angles of task t_i $Pitch_i = \sum_{j=1}^{N_S}\sum_{k=1}^{N_{ij}}\sum_{v=1}^{N_{ijk}} x_{ijkv} * pitch_{ijkv} \Big/ N_{ijk}$

The average roll angles of task t_i $Roll_i = \sum_{j=1}^{N_S}\sum_{k=1}^{N_{ij}}\sum_{v=1}^{N_{ijk}} x_{ijkv} * roll_{ijkv} \Big/ N_{ijk}$

So, if task t_i is not selected, $Pitch_i = Roll_i = 0$;

$$ImageQuality = \min\left(\sum_{i=1}^{N_T} (Pitch_i + Roll_i)\right);$$

- Load balance of each satellite: minimize the standard deviation of each satellite load (selected tasks)

Load of Satellite s_j $Load_j = \sum_{i=1}^{N_T}\sum_{k=1}^{N_{ij}} x_{ijk}$;

Average load of each satellite $Load_{ave} = \sum_{i=1}^{N_T}\sum_{j=1}^{N_S}\sum_{k=1}^{N_{ij}} x_{ijk} \Big/ N_S$;

$$Balanceload = \min\left(\sum_{j=1}^{N_S} | Payload_j - Payload_{ave} |\right);$$

- Task number: minimize the number of unselected tasks

$$TaskNumber = \min\left(N_T - \sum_{i=1}^{N_T}\sum_{j=1}^{N_S}\sum_{k=1}^{N_{ij}} x_{ijk}\right)$$

D. Constraints

Here are constraints which

$$\forall i \in O : (x_i = 1) \Rightarrow (a_i \le St_i \le b_i) \qquad (1)$$

$$\forall i, j \in O : (f_{ij} = 1) \Rightarrow St_i + d_i + TS_{ij} \le St_j \qquad (2)$$

$$\forall t_i \in T : (x_{ijkv} = 1) \Rightarrow x_{ijk} = 1, \sum_{v=1}^{N_{ijk}} x_{ijkv} = N_{ijk} \qquad (3)$$

$$\forall t_i \in T : \sum_{i=1}^{N_T}\sum_{j=1}^{N_S}\sum_{k=1}^{N_{ij}} x_{ijk} \le 1 \qquad (4)$$

The constraint (1) is time window constraint. The constraint (2) is satellite attitude maneuver time constraint. The constraint (3) expresses all strips in an opportunity of one task must be observed all or not. The constraint (4) states that we need observe task t only once.

IV. Algorithm

The AEOS multi-objective mission planning problem we faced is very complicated, in which four objectives contribute to the overall result. These objectives affect one another in complex, nonlinear ways. Analysis of the problem reveals four critical pieces:

1) What order should the tasks be (to wait for scheduling)?
2) Which opportunity should be selected for the task?
3) How to estimate the task can be observed in a selected opportunity and fix the exact start time?
4) How to evolve and optimize the scheduling result?

The combinatorial explosion is obvious, and obtaining exact optimal solutions for this type of NP-hard problems is computationally intractable. Evolutionary computation has been widely applied to solve multi-objective optimization[10].Their success resides in the general applicability of evolutionary algorithms in finding good solutions to problems with appropriate structure, and the adaptability of genetic representation and fitness evaluation towards problems in the MOP field.

In this paper, we use SPEA2[11] algorithm to solve the multi-objective mission planning problem. SPEA2 has shown very good performance in comparison with other multi-objective evolutionary algorithms[11]. In the algorithm, we use individual coding strategy to solve the problem 1 and 2, decoding strategy based on backward time slack to solve problem3, evolution strategy to solve the problem 4. The main loop of the algorithm is in figure 4.

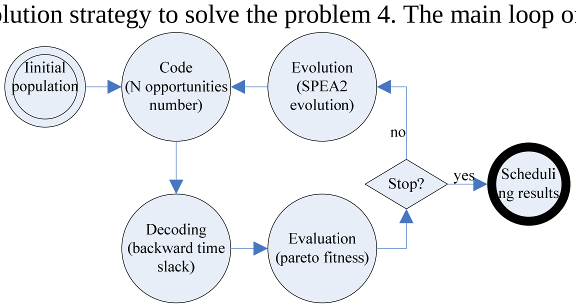


Figure 4. the main loop of the algorithm

A. Individual Coding Strategy and Initial Population Creation

In order to apply the SPEA2 to a particular problem, we need to select an internal string (individual) representation for the solution space. The choice of this component is one of the critical aspects to the success/failure of the evolutionary computation for a problem of interest. In our approach, an individual is given by an integer string of length N, where N is the number of observing opportunities. A gene in a given individual indicates the observing opportunities number of task assigned to a satellite, whilst the sequence of genes in the individual string dictates the order of tasks to be scheduled, see Figure 5.

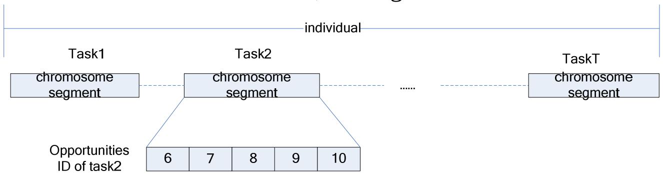


Figure 5. chromosome representation

To generate the initial population, four individuals are generated by a greedy procedure as follows, others are created by random permutations of N opportunities number.

1) chronological forward of N opportunities;
2) chronological backward of N opportunities;
3) sorting by weight of N opportunities from high to low;
4) sorting by weight of N opportunities from low to high.

B. Individual Decoding Strategy

Decoding strategy is used to estimate if the task can be observed in selected opportunity and fix the exact start time. Figure 6. give a simple example of Insert tasks and compute backward slack time. The main loop of individual decoding strategy is as follows:

Input: individual

Output: scheduling result

Step1: select opportunity in the order of individual, and select the earliest start time of the opportunity as the task's initial start observing time;

Step2 : insert task by selected opportunity in single satellite scheduled task queue, computing exact start time and backward slack time in every position of satellite task queue, computing method can be seen in references[12, 13];

Step3 : select the position which has max backward slack time; if the max backward time is less than zero, indicate that the task can not be arranged in this opportunity, skip it;

Step4: repeat step1-3 until all opportunities of individual are attempted;

Step5: adjust the scheduled tasks in task queue, minish the observing pitch angle of every task as possible.

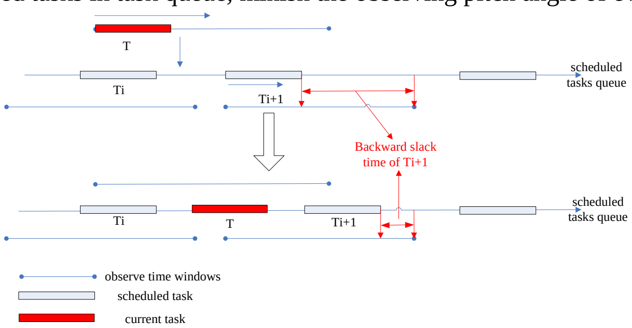


Figure 6. Insert tasks and compute backward slack time

C. Evolution Strategy

Details of evolution strategy we use can be seen in reference[11], including fitness assignment, environmental selection, crossover and variation. The novelty of the evolution strategy is that we design the adaptive probability for crossover and variation. And we also setup the population replace strategy. Along with the evolution, the probability will decrease and part of the population will be replaced by random created individuals.

D. Stop criterion

We use the maximum number of generation as our stop criterion.

V. Simulation and Experimental Results

The AEOS multi-objective mission planning problem we faced has many differences with other studies in EOS domain, so it is problematic to evaluation the EA algorithm with other algorithms. However, we create realistic instance with the help of STK (Satellite Tool Kit). The satellite constellation we consider is made up of three identical satellites moving on the same orbit (circular, low altitude, and heliosynchronous) with a phase shift of 120 degrees between each satellite. The provided instance is artificially generated, with 200 tasks, 2082 strips, and 912 opportunities. The weight of tasks are 1-5 and are randomly given to the tasks, 5 is the highest weight. The average difference between the earliest starting time and latest starting time of an image is about 220 seconds. The duration of an image acquisition is about 10 seconds, and the typical transition time between the acquisitions of two successive images is 30 seconds. Targets are distributed randomly in earth surface. Figure 7. shows targets distribution. For the instance, we use two days planning horizon. By the way, the algorithm is implemented in C# language and compiled using visual studio 2005. The experiments were carried on a Pentium 4 CPU 3.0 GHz PC with 2 GB of RAM. The algorithm parameters are as follows: population size of individual is 1000; archive size is 100; recombination of 0.5, mutation of 0.1.

Figure 7. Targets Distribution

In order to compare the algorithm, we first use single objective function to run the algorithm and get near optimize results. The evolution process can be seen in Figure 8. and the near optimize results are (117, 3341.4, 0, 52).

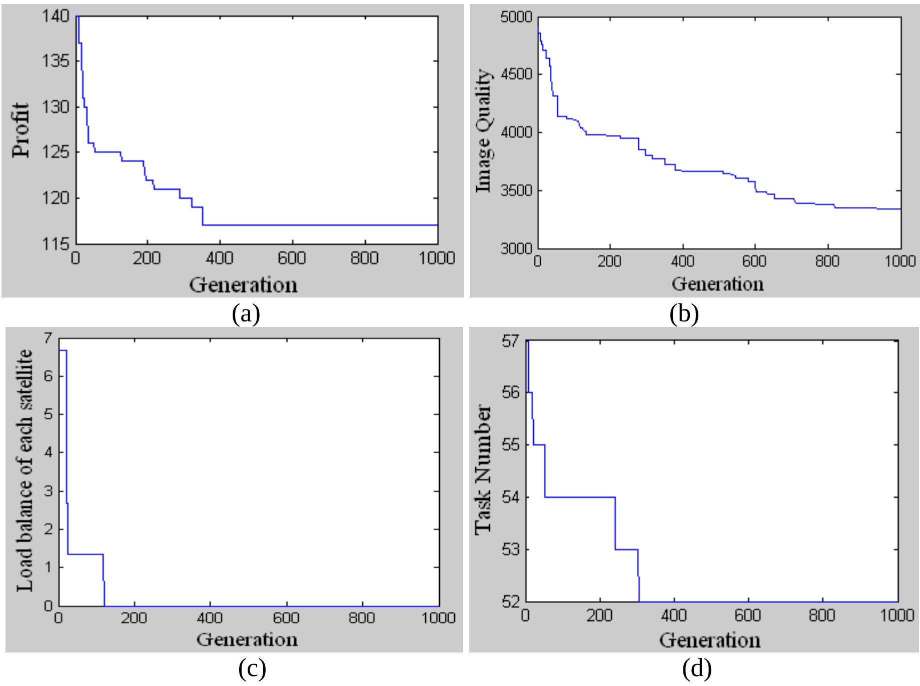
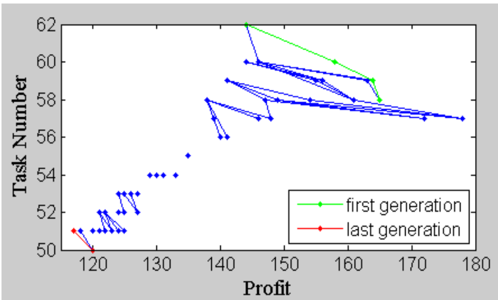


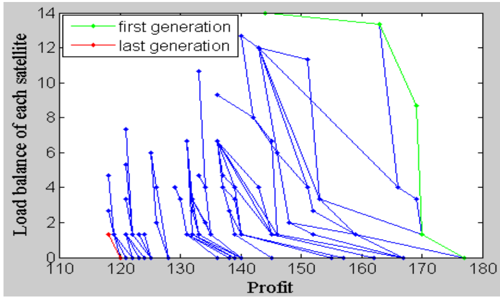
Figure 8. Results of single object

Then we choose four groups of objective functions to run the algorithm. They are profit and task number, profit and load balance of each satellite, task number and image quality, profit and image quality. See Figure 9. , the green line denotes the first generation pareto group and the red line denotes the last generation pareto group. For the first two object groups, our algorithm is convergent to a few Pareto optimal solutions; for the other two groups, our algorithm can give good Pareto front.

Generally speaking, single object mission planning results would be better than multi-objective planning because the latter spend much energy in finding pareto front. Compare to the single objective planning, we can see that multi-objective mission planning results is very close to the single objective mission planning results except the image quality object, some results are even better than the single objective mission planning, see Figure 9. (a). The results validate the efficiency of our approach. The gap of the image quality object is large (about 30%) between single and multi-objective planning, we think there are two reasons. First, this object has more conflict with the other objects. Second, the decoding strategy we use in the algorithm is insert task first and then improve the image quality, this may further increase the gap.



(a)



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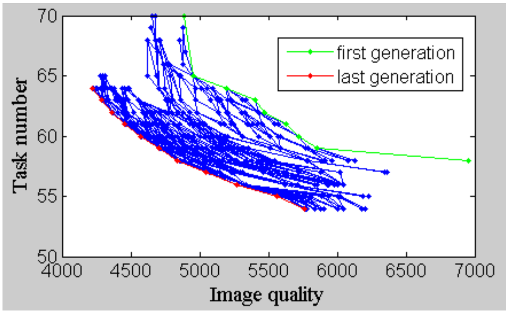

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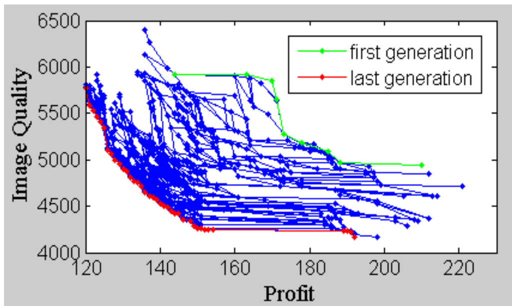

(d)

Figure 9. Results of multi-objective planning results

VI. Conclusion

In this article, we describe multi-objective mission planning problem of the new generation of agile Earth observing satellites. Four criteria including profit, image quality, load balance of each satellite and task number, are given to evaluate the schedule results. Evolutionary algorithm is designed to solve the problem with special individual coding and decoding strategy. Simulation and experimental results show that our model and algorithm can effectively solve the problem. Development of the current work, such as consider all the criteria and design more effective algorithm, could be done in future studies.

Appendix A
Acronym List

EOS Earth Observing Satellite
AEOS Agile Earth Observing Satellite
SPEA2 Strength Pareto Evolutionary Algorithm

Acknowledgments

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