Preference-based Evolutionary Algorithms for Many-Objective Mission Planning of Agile Earth Observation Satellites

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ABSTRACT

The mission planning of agile earth observation satellite (AEOS) involves multiple objectives to be optimized simultaneously. Total profit, observed target number, averaged image quality, satellite usage balance and averaged timeliness are the five objectives considered in this paper. The problem is a mixed-integer problem with constraints and belongs to the class of NP-hard problems. Two preference-based evolutionary algorithms, i.e., T-NSGA-III and T-MOEA/D, are proposed with problem-specific coding and decoding strategies to solve the problem. Target region, which is defined by preferred range of each objective, is used for preference articulation. Experiments show that the proposed algorithms can obtain Pareto optimal solutions within the target region efficiently. They outperform Pareto-based T-NSGA-II with regard to Hypervolume indicator and CPU runtime.

CCS CONCEPTS

• **Applied computing** → **Multi-criterion optimization and decision-making**; • **Mathematics of computing** → *Bio-inspired optimization*;

KEYWORDS

Agile Earth Observation Satellite; Satellite Mission Planning; Evolutionary Multiobjective Optimization; Preference; MOEA/D

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1 INTRODUCTION

The mission of Agile Earth Observation Satellite (AEOS) is to acquire photographs of the earth surface in response to user requests. The access window (when the satellite is close enough to take images) of AEOS is much longer than requested, the mission planning has to decide not only which targets to observe, but also when to start the observation. As we know, heuristic and metaheuristic approaches are often investigated by researchers and engineers to solve the problem. One of the common drawbacks is that they aim at an approximation of the whole Pareto front, without consideration of the decision making process. Recently, Li et al. introduced preference incorporation in multi-objective AEOS mission planning [4, 5]. However, with the development of aerospace technologies, more objectives should be involved in the planning, to achieve a plan satisfied by both image users and satellite control agencies. In this paper, we extend the idea of preference-based evolutionary algorithms for many-objective AEOS mission planning. Two more objectives are considered and two state-of-the-art multi-objective evolutionary algorithms, i.e., NSGA-III [1] and MOEA/D [2], are modified to embed the preference information and applied to the AEOS mission planning problem.

2 PROBLEM FORMULATION

We adopt the same notations and constraints as in [5]. Apart from profit, quality and balance, two more objectives are also considered.

- **Quantity**: maximize the total number of the observed targets.

$$|OT| \rightarrow \max$$

- **Timeliness**: maximize the averaged timeliness metric for all the observed targets.

$$\frac{1}{|OT|} \sum_{ot \in OT} ot.ti \rightarrow \max$$

where ti depends on how many access windows can observe this target and the rank of this window by chronological order. The earlier this window ranks, the bigger ti is.

3 PROPOSED APPROACH

Recently, two target region-based evolutionary algorithms (T-NSGA-III and T-MOEA/D) were proposed for many-objective optimization (when there are more than three objectives) [3]. We apply them to AEOS mission planning problem and propose a problem-specific integer coding approach. A solution is represented by an integer array in the length of target number (N). Each integer corresponds to one target, if the integer is non-zero, it indicates the chosen access window. If the integer is zero, no satellite will observe this target. This representation only decides which access windows to

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Table 1: Problem Instances

Problem instance	Task Count	Access Count	Distribution	Target region
1	50	251	C	{(0.7,0.6,0.8,0,0),(1,1,1,0.5,1)}
2	50	266	R	{(0.9,0.9,0.9,0,0),(1,1,1,0.5,1)}
3	100	512	C	{(0.0,0.0,0.8,0,0.7),(0.6,0.6,1,0.5,1)}
4	100	576	R	{(0.8,0.8,0.8,0,0.8),(1,1,1,0.3,1)}
5	150	762	C	{(0.0,0.0,0.8,0,0.7),(0.6,0.6,1,0.6,1)}
6	150	820	R	{(0.7,0.7,0.8,0,0.5),(1,1,1,0.3,1)}
7	200	1009	C	{(0.0,0.0,0.9,0,0.5),(0.5,0.5,1,0.5,1)}
8	200	1128	R	{(0.8,0.8,0.8,0,0.5),(1,1,1,1,1)}

Table 2: Mean and standard deviation of HV within the target region in 20 independent runs

Instance	T-NSGA-III	T-MOEA/D	T-NSGA-II
1	1.350e-3(9.47e-4)*	1.232e-3(1.25e-3)*	1.194e-4(4.51e-4)
2	0.12806(0.0358)	0.06016(0.0565)	9.54e-3(0.0280)
3	0.01585(6.77e-3)*	0.01326(6.44e-3)*	5.724e-3(3.67e-3)
4	0.07933(0.0418)*	0.04527(0.0404)*	2.845e-3(4.01e-3)
5	8.611e-3(2.02e-3)*	7.814e-3(2.47e-3)*	2.929e-3(1.31e-3)
6	0.11309(0.0581)	0.05068(0.03541)	7.620e-3(0.0112)
7	8.141e-3(4.55e-3)*	0.01239(3.93e-3)*	4.103e-3(1.68e-3)
8	0.01777(0.0108)*	0.01606(7.38e-3)*	0.00000(4.46e-5)

choose, when to start the observation will be determined in the decoding strategy using some heuristic rules.

The two-point crossover is adopted. Two crossover points are selected randomly and all the integers between the two points are swapped between the two parents. The single-point mutation is employed. One integer is selected randomly using the specified probability. The chosen integer will change to a different value in the candidate set.

4 NUMERICAL STUDIES

Eight problem instances are designed for the experiments using System Tool Kit (STK). The target number ranges from 50 to 200, the access window number ranges from 251 to 1128. More targets correspond to more access windows. There are two kinds of distribution of the targets: randomly distributed all over the world (R), concentrated distributed inside the mainland of China (C). For each problem instance, a target region is used to stress one or two objectives after checking the approximate PF. Table 1 lists the target number and distribution, access window number, and the chosen target region for every problem instance. T-NSGA-II [6] is adopted as a comparative algorithm for it shares the same preference articulation as the proposed algorithms.

From the graphical figures we can observe that T-NSGA-III and T-MOEA/D can obtain solutions complying with the preferences in all the problem instances. T-NSGA-II fails to find solutions within the target region in instance 8. In instance 1 to 7, T-NSGA-III and T-MOEA/D have better diversity than T-NSGA-II. To compare the three algorithms quantitatively, we use Hypervolume indicator (HV) within the target region as a measure. Each algorithm is executed for 20 independent runs and the Kruskal-Wall test is employed to check the indifferent algorithms. The mean and standard deviation of HV in 20 runs are shown in Table 2. The best algorithm is marked with dark gray background and the second is in light gray background.

From Table 2 we can observe that T-NSGA-III and T-MOEA/D are indifferent to each other in 6 instances, they both have better HV than T-NSGA-II. In instance 2 and 6, T-NSGA-III is better than T-MOEA/D, T-NSGA-II still has the worst performance.

We also compare the CPU runtime and find that, the averaged runtime increases with the scale of the problem. T-NSGA-II has the longest runtime among the three algorithms except for instance 8, where it fails to converge within the target region. T-MOEA/D is faster than T-NSGA-III for all the instances.

Conclusions can be drawn that compared to T-NSGA-II, T-NSGA-III and T-MOEA/D have stronger capabilities in finding solutions within the target region, and consume less time. T-NSGA-III performs slightly better than T-MOEA/D in terms of HV metric. However, T-MOEA/D is slightly faster than T-NSGA-III considering the averaged runtime.

5 CONCLUSIONS

In this paper, we have investigated the many-objective satellite mission planning problem with the help of preference-based evolutionary multi-objective algorithms. Five objectives are considered simultaneously: total profit, total number of observed targets, averaged quality, resource balance and averaged timeliness. A target region, which is defined by preferred range of every objective, is adopted to express the preferences of the DM. Two state-of-the-art algorithms, i.e., T-NSGA-III and T-MOEA/D, are applied to find Pareto optimal solutions that are of interest to the DM. Problem-specific coding and decoding strategies are proposed for solving the problem. Experiments have shown that T-NSGA-III and T-MOEA/D successfully converge to Pareto optimal solutions within the target region, they outperform T-NSGA-II with regard to Hypervolume indicator and CPU runtime.

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