

Task scheduling method of revisit tasks for satellite constellation towards wildfire management

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Global warming increases forest wildfire risks to the economy, environment, and human safety. Continuous satellite monitoring offers accurate wildfire predictions and data-driven decision support. Earth Observation Satellite Constellations (EOSC) enable periodic wildfire tracking through revisit observations. Efficient scheduling of these tasks is crucial for optimal constellation operation in wildfire management. However, the existing EOSC scheduling algorithms rarely concentrate on the scheduling of revisit tasks. In this paper, the revisit task scheduling problem of the EOSC is expressed as a multi-objective model. A time-driven multi-objective optimization method (TDMO) is designed to optimize the constellation scheduling process of wildfire observation tasks. TDMO has a time-driven feature and coupled with revisit time in the task, experiments on different scheduling scenarios show this method is effective in scheduling revisit tasks towards wildfire targets.

Introduction: Wildfires pose significant hazards due to their large scale, rapid development, and swift spread, necessitating effective monitoring methods. EOSC, with its broad coverage and spectral diversity, is suitable for wildfire monitoring. EOSC has an important capability in revisit time, which refers to the time interval between successive visits over the same location on the Earth's surface. Revisit observations are crucial for wildfire detection and monitoring. Periodic revisit tasks and large scale of constellations pose challenges to task allocation, effective and rapid scheduling is key to maintaining stability revisit services for EOSC.

The task scheduling method for the EOSC is designed to optimize the observation profit while considering various complex constraints, which give full play to the overall effectiveness of the EOSC. It is known to be NP-Complete[1]. Several researchers have investigated the task scheduling method of EOSC. Some use mixed integer linear program formulation to build a mathematical model for the EOSC scheduling problem[2, 3, 4, 5, 6, 7], to solve the formulation and decomposed the issue as a master problem and multiple pricing problems.

Some studies divide the EOSC scheduling problem into task allocation and scheduling, focusing on the setting of allocation rules[8, 7, 9].

However, none of these researchers scheduled the revisit tasks for the EOSC. Moreover, most of the satellite constellations studied are relatively small, typically consisting of around a dozen satellites [10, 11, 12, 13, 14, 15]. Also, researchers studying multi-objective satellite scheduling problems have not considered the scheduling of revisit tasks[16, 17, 18, 19].

As the size of EOSC increases, the complexity of the scheduling problem grows exponentially. This increased complexity arises from the need to manage more potential task assignments, more frequent revisit requirements, and a greater number of constraints. Consequently, multiple conflicting objectives must be considered simultaneously, such as maximizing observation profits, ensuring timely revisits, and optimizing resource utilization. The previously proposed methods, which were effective for smaller constellations, fail to scale efficiently and do not provide multi-objectives solutions of revisit tasks for larger constellations.

In this letter, we propose the Time-Driven Multi-Objective (TDMO) method to schedule wildfire observation tasks for large-scale EOSC, aiming to dispatch all satellites in the constellation to continuously maneuver and revisit wildfire targets. With this method, the revisit cycle is also considered during the task allocation process, making the distribution of revisit tasks more efficient and ensuring timely and effective wildfire monitoring.

Objectives: Our scheduling goal is to make the constellation finish the revisit observation efficiently. Regarding wildfire observation, we aim to maximize the total number of wildfire targets revisited throughout the scheduling horizon. On the other hand, minimizing the number of observation tasks assigned to the target is necessary to ensure the observation efficiently. In terms of satellite utilization, it is critical to minimize the working time of the satellite and the uniformity of task distribution for each satellite. This can extend the life of the constellation.

Considering the complex observation goals, a multi-objective mixed integer model for the scheduling problem is constructed. Four objectives are included in the optimization model.

- The objective of maximizing the number of revisited targets in the scheduling horizon can be expressed as follows:

$$\text{Maximize}(n_{tar}) \quad (1)$$

Where n_{tar} represent whether the number of target completes the revisit in scheduling horizon.

- The objective of minimizing the number of observation tasks can be expressed as:

$$\text{Minimize}(n_{task}) \quad (2)$$

Where n_{task} is the number of task conducted in scheduling horizon.

- The objective of minimizing the satellite working time can be expressed as follows:

$$\text{Minimize}(S_{wk}) \quad (3)$$

Where S_{wk} represents the total maneuvering time of all satellites in the constellation.

- The objective of minimizing the uniformity of tasks distribution can be expressed as follows:

$$\text{Minimize}(\sigma_{sat}) \quad (4)$$

Where σ_{sat} represents the variance of all satellite maneuvering time.

Owing to the task specifications and the constrained resources of the satellite, the above models are subject to many constraints. First, each task has a visible time window (VTW), and the execution time of the task should be within the time window. Second, the attitude transition needs to be conducted for the EOS satellite. And Enough maneuvering time is required between two consecutive tasks. Thirdly, the interval between two observations for each revisit task must not be less than the observation interval specified by the task.

Method: As shown in Figure(1), the TDMO method would follow the allocation and task scheme generation in the evaluation process. The process begins by inputting the satellite and target information. The satellite information can be represented to $n_{sat}, \{sid, v\}$. n_{sat} is the number of the satellite. Each satellite contains. Where the sid represents the identity of observation satellites, v is the maneuver rate of the satellite. Wildfire targets information contains $n_{tar}, \{tid, vtw, t, re\}$. Where n_{tar} represents the quantity of all targets, tid is the, identity of observation targets, vtw is the information of all VTWs. t is the current scheduling time and re is the revisit time of the target. Then, TDMO is used to initialization and evolution the task allocation process.

The task allocation method based on heuristic rule

Figure(1b) shows the task allocation process. For each target, calculate all the VTWs during the scheduling horizon to compose the task information. Then, we conduct a task allocation process for all the targets in the scheduling scenario, which is driven by the revisit time as a cycle. A scheduling horizon can be divided into multiple revisit cycles, each cycle is allocated according to time sequence.

For current target in task allocation process, all observation time windows within the revisit period are selected. Moreover, we truncate the time window that exceed the revisit period. Then, the assignment rule based on the scheduling objectives is performed to ensure that the observation is conducted in the most suitable time window and satellite. After the allocation of current target, the allocation process will conduct to next target in the revisit cycle.

The allocation factors are shown as follows:

- 1 The time gap is the interval between the target's last observed time and the current task's start time.

$$par_1 = vtw_{i-1} - vtw_i \quad (5)$$

par_1 indicates the time difference between the selected time window vtw_i and the previous observation window vtw_{i-1} , which reflects the length of time that the target has not been observed. To finish the revisit requirement with fewer observation tasks, the time difference between target observation tasks should be close to the revisit time cycle.

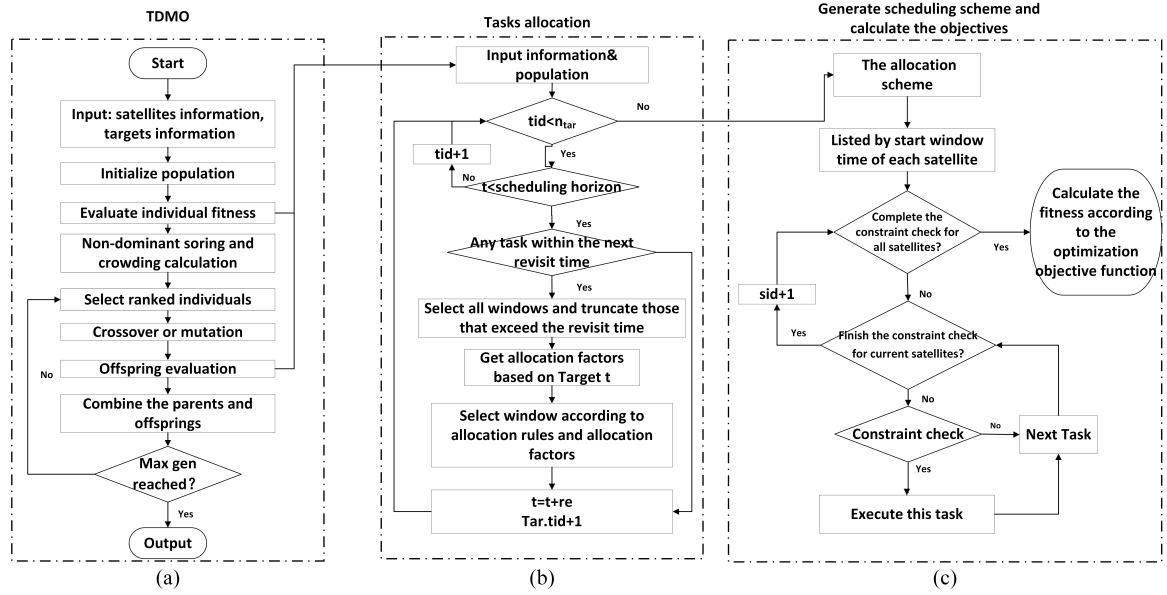


Fig. 1. Flowchart of TDMO.

2 The uniformity of task distribution for current satellite implementation

$$par_2 = \frac{\sum_i^{n_{task}} y_{task_i}}{(y_{sat} + 1) * n_{sat}} \quad (6)$$

$\sum_i^{n_{task}} y_{task_i}$ represents the total number of tasks that have been assigned. y_{sat_j} indicates the number of tasks assigned to the current satellite. par_2 represents the uniformity of the current distribution. In the process of task allocation, it is imperative to distribute tasks as uniformly as possible. Ensuring that the operational duration of each satellite is consistent contributes significantly to enhancing the overall lifespan of the constellation.

3 Current maneuvering angle Δg .

$$par_3 = \begin{cases} 0 & (Figure2a) \\ \Delta g_m + \Delta g_{m+1} - \Delta g_n & (Figure2b) \\ \Delta g_m & (Figure2c) \\ \Delta g_{m+1} & (Figure2d) \end{cases} \quad (7)$$

The assignment process in this paper is driven by the target's revisit cycle, where new tasks are inserted into the satellite's original task sequence during each cycle. The large scale of the constellation usually offers multiple task options. A key factor in task selection is the duration of attitude maneuvers, as varying maneuver angles lead to different maneuver times. Minimizing these maneuvers is crucial for efficient task execution. Four situations will be generated caused by the task's different insert positions, leading to different maneuvering times as shown in Function(7). Δg_m is the required maneuvering angle from the previous task to the current inserted task, and Δg_{m+1} is the transfer time from the current inserted task to next task. When the newly inserted task is on the maneuver path of the original sequence, the execution impact on the satellite maneuver is minimized, as shown in Figure(2a). Otherwise, As shown in Figure(2b), when the inserted task is out of the maneuver path, the satellite needs more attitude maneuvers to complete the observation, and Δg_n is the time required for the original maneuver. Where the inserted task is at the front or end of the task list, as shown in Figure(2c) and Figure(2d), and the transfer time required is Δg_m and Δg_{m+1} .

According to the allocation rules, we can calculate the probability of assignment of the corresponding task as follows:

$$p = \sum_{i=1}^3 par_i * val_i \quad (8)$$

Where val_i represent the weight of each assignment rule. TDMO is designed to find appropriate allocation weights within the revisit period-driven allocation cycle. Thus, an initial population of potential solutions is generated. We set the chromosome to the weight of each assignment rule as shown in Function(8).

The assignment weights are vary from 0 to 1. In the scheduling process, we divide the scheduling horizon into multiple period based on the revisit time. The assignment parameters for each period are represented by the corresponding gene fragment T_n . Where T represents the update cycle of assignment parameters. Allocation parameters can be changed during the scheduling horizon by setting update cycles based on the revisit time, making the scheduling process more flexible. When the number of update cycles increases, the degree of flexibility in the allocation process increases. However, the chromosome length also becomes longer and the difficulty of the solution increases. How to effectively trade-off to find out the appropriate update cycle is also one of the focuses of this study.

Task scheme generate

After the task allocation process, the revisit task for each target would be assigned to satellites and generate the allocation scheme. As shown in Figure(1c), we perform a constraint checking process to ensure that there are no conflicts between tasks in the scheme.

For each satellite in the scheduling scenario, sort all tasks by the start time, then conduct the constraint check until we arrange all the tasks in the scheduling scenario. We conduct the task at the earliest non-conflicting moment within the VTW. When the current task fails to execute, we would perform constraint checking for the next task. After completing the constrain checking process, the scheduling result is output.

Each solution is then evaluated based on the objective function1, 2,3 and 4. The individuals in the population are sorted using non-dominant sorting to ensure Pareto efficiency and crowding distances are calculated to maintain diversity. Top-ranked individuals are selected for reproduction through genetic operations. Simulated Binary Crossover and polynomial mutation are used in genetic algorithms to generate new offspring solutions from two parent solutions. In TDMO, assignment parameters from the same update cycle are involved in these operators. The offspring are then evaluated, and the combined population of parents and offspring is assessed to select the best individuals. This iterative process continues until the maximum number of generations is reached, resulting in the optimal task scheme.

Results: The seed satellites are placed in a circular orbit at an altitude of 650 km with an inclination of 80 degrees. The chosen constellation configuration is 100/25/8, and the satellite maneuver rate is set to 2 degrees per second. We developed a wildfire target database with three

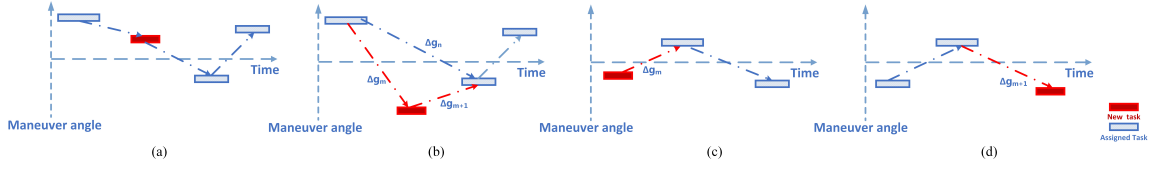


Fig. 2. Transition time of different task.

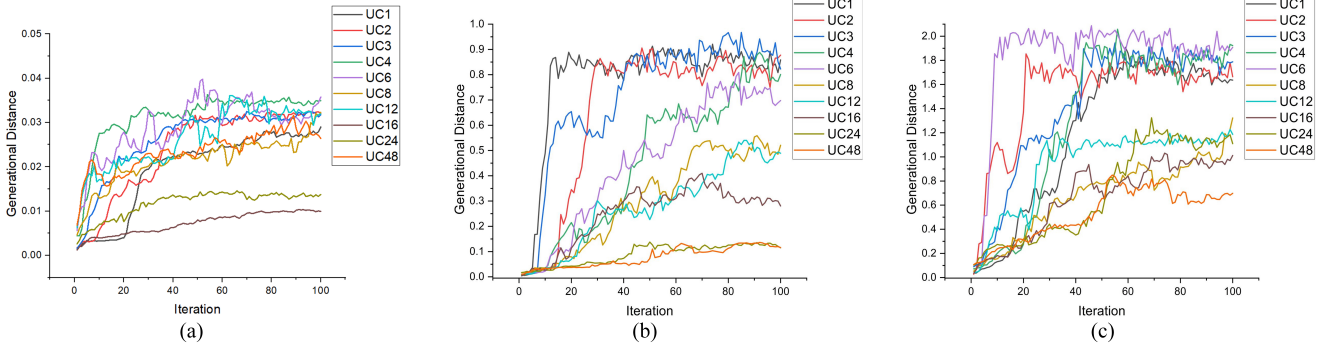


Fig. 3. Iteration process of the TDMO.

models: global distribution during non-peak season (50 targets), global distribution during peak season (200 targets), and regional distribution (50 targets). To ensure better observational continuity, the revisit time for wildfire targets is set to 30 minutes. The scheduling horizon is one day, with each target requiring at least 48 observations. The update cycle frequency determines how often allocation parameters are updated. For example, with an update cycle of 2, updates occur twice daily. The chromosome length is six, representing two cycles: T1 and T2. Allocation parameters in T1 cover the period from 0-12 hours, while those in T2 cover 12-24 hours.

Simulations Results and Analysis

According to the chromosome design methodology mentioned in Section , we can set different update cycles for the allocation parameters to increase flexibility in the allocation process. The sequence of update cycles is chosen to be a common divisor of 48 (the number of target revisits). Generational Distance (GD) is used to assess the TDMO method. GD measures the distance between the obtained solutions and the true Pareto front, reflecting the set of optimal solutions for the given problem. Obtaining a true Pareto front is challenging in the revisit task scheduling problem for larger-scale EOSCs. Therefore, we use initial populations to estimate the evaluation of TDMO. A larger value of GD indicates better convergence to the Pareto-optimal front.

Scenario 1: Task scheduling on the regional distribute targets

In scheduling scenarios for regional distribute targets, the iteration process of the scheduling is shown in Figure(3a). The horizontal axis of Figure(3a) indicates the number of iterations of TDMO, and the vertical axis represents the GD. As shown in the Figure(3a), the rewards increase along with the increment of the iteration process and gradually converge to a fixed value, indicating that TDMO effectively optimizes regionally distributed wildfire targets. The change in the update cycle(UC) from 1 (UC1) to 48 (UC48) for the allocation parameters significantly impacts the iteration results. Initially, as the update cycle increases, the maximum GD (MAXGD) value also increases, demonstrating the effectiveness of more frequent assignment parameter updates in the scheduling of revisit tasks. However, as the number of parameter updates continues to rise, the value of MAXGD starts to decrease. This occurs because the length of the chromosome increases with the number of updates, leading to a dramatic expansion of the solution space, which complicates the search process and results in poorer optimization.

Scenario 2: Task scheduling on the 50 global distribute targets

As seen in Figure (3b), similar to the locally distributed target scenario, the MAXGD is larger at intermediate UC. The convergence values of the

iterations are generally higher than those for locally distributed targets, suggesting that the algorithm achieves better results and offers more optimization space when the target is globally distributed.

Scenario 3: Task scheduling on the 200 global distribute targets

Figure (3c) shows that GD values rise quickly and converge rapidly, demonstrating the algorithm's effectiveness in optimizing scenarios with a large number of targets. The MAXGD occurs at medium UC and is significantly higher than in scenarios with fewer targets. As the number of targets increases, the solution space expands dramatically, allowing TDMO to search for better solutions. The increase in GD values highlights the algorithm's ability to find optimal solutions in a larger solution space.

Table 1: Comparison of results for each objective.

Algorithm	NSGA-II			TDMO		
Scenario	1	2	3	1	2	3
MAXGD	0.024	0.74	1.61	0.035	0.96	1.92
n_{tar}	50	50	200	50	50	200
n_{task}	3610	3616	14701	3281	3046	11846
S_{wk}	5.58	6.77	39.14	4.93	5.99	34.63
σ_{sat}	0.026	0.032	0.12	0.022	0.025	0.067

Comparison Simulation

Table (1) lists the optimal scheduling results for NSGA-II and TDMO for different objectives (Obj1 Obj4 as defined in Section 2). Compared to NSGA-II, TDMO significantly optimizes the objectives and maximum generational distance (MAXGD) after iterative optimization with an appropriate number of parameter updates. In the GLOBAL200 scenario, TDMO reduces the workload by 20%, significantly enhancing observation efficiency while meeting revisit requirements. Additionally, there is a noticeable improvement in task distribution uniformity across all three scenarios. This demonstrates TDMO's effectiveness in selecting appropriate allocation parameters for flexible scheduling and achieving desired results.

Conclusion: In this study, we designed a revisit tasks scheduling method for the large EOSC based on multi-objective optimization. TDMO is proposed to optimize the allocation parameters, using a periodic update design for the allocation process. This method is effective in different scheduling scenarios and can efficiently optimize the allocation parameters, leading to better scheduling results. After the optimization, the EOSC task planners can select the appropriate combination of allocation parameters to schedule for the corresponding objectives.

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