Scheduling Optimization Method for Space Debris Monitoring Network Under Multiple Monitoring Tasks (Postprint)

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Date: 2024-01-05T00:00:00+00:00

Abstract

Orbital measurement data collected by the space debris monitoring network constitute the foundation for orbital cataloging. Confronted with massive debris populations and limited monitoring stations, data acquisition methods and rapid operational mission scheduling optimization represent key technologies for fully exploiting monitoring effectiveness and improving cataloging capability and accuracy. Monitoring tasks encompass routine monitoring, priority target monitoring, and emergency monitoring, among others. To address the multi-task scheduling optimization problem for monitoring networks, we propose a linear assignment model and a nonlinear assignment model incorporating movement costs, both utilizing monitoring benefit as the objective function, and solve them using an improved LAPJV algorithm and an improved 2-opt algorithm. Simulation experiments on space debris monitoring mission optimization for ground-based observation networks were conducted. The linear and nonlinear models processed 4-hour mission planning for 200 stations and 7,170 debris fragments. The improved LAPJV algorithm and 2-opt algorithm achieved solution times of 12.051 s and 162.071 s, respectively, yielding total monitoring benefits of 289,399.07 and 285,333.79, respectively, and enabling the monitoring of 2,931 and 2,918 debris fragments, respectively, which accounts for over 40% of the total debris population. The results demonstrate that the models/algorithms achieve a balance between solution speed and accuracy, possess near-real-time monitoring mission optimization capability, and can serve as an effective solution for monitoring mission optimization.

Full Text

Preamble

Vol. 41, No. 4

December 2023

Progress in Astronomy Vol. 41, No. 4 Dec., 2023 doi: 10.3969/j.issn.1000-8349.2023.04.09

A Scheduling Optimization Method for Space Debris Monitoring Network in Multiple Monitoring Task Scenarios

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Abstract

Orbit measurement data collected by a space debris monitoring network is the basis of debris orbit cataloguing. With the vast number of debris objects but limited monitoring facilities, data collection strategy and rapid task scheduling optimization are key technologies to fully leverage monitoring capabilities and improve cataloguing capacity and accuracy. Monitoring tasks include routine monitoring, priority target monitoring, and emergency monitoring. For the multi-task scheduling optimization problem of a monitoring network, this paper proposes a linear assignment model and a nonlinear assignment model considering move cost, respectively, in which the monitoring benefit is defined as the objective function, and uses the improved LAPJV algorithm and improved 2-opt algorithm to solve them. Optimization experiments with ground-based simulated debris monitoring networks are carried out, in which the improved LAPJV algorithm and 2-opt algorithm have a solution time of 12.051 s and 162.071 s, respectively, and the total benefit is 289,399.07 and 285,333.79, respectively, in terms of the linear model and the nonlinear model with 4-hour task scheduling for 200 stations and 7,170 debris. The final results show that both algorithms are able to solve near real-timely the monitoring task programming, and can be used as an effective solution to the network task scheduling optimization.

Key words: space debris; monitoring and maintenance; scheduling optimization/programming; LAPJV; k-opt

1 Introduction

As human space exploration activities become increasingly frequent, the near-Earth space environment is gradually deteriorating. According to data from the European Space Agency (ESA) as of November 2022, the Space Surveillance Network (SSN) has catalogued approximately 32,190 space objects, of which only about one-quarter are active payloads, with the majority being space debris. NASA models estimate that there are over one million debris objects larger than 1 cm, and hundreds of millions smaller than 1 cm. In particular, recent mega-constellation projects such as Starlink and several major collision and breakup events have placed higher demands on space object cataloguing and monitoring. Space target monitoring systems play a fundamental role in both military and civilian applications. In military applications, they enhance reconnaissance and early warning capabilities for security threats, including monitoring space targets with military significance, tracking their orbital status and payload characteristics, monitoring global space launch activities, obtaining ballistic missile data, detecting, tracking, and identifying unknown flying objects, and providing early warning for potential debris collisions and threats to friendly satellites. In civilian applications, they enable effective monitoring of key civil aircraft and serve as a powerful supplement to ground-based monitoring, providing timely fault monitoring for spacecraft to ensure safe operations.

In the field of debris monitoring, to reduce collision risks, protect the safety of spacecraft in orbit, and achieve sustainable utilization of space resources, it is essential to conduct routine space debris monitoring and cataloguing and perform collision risk assessment for spacecraft. Meanwhile, certain high-value or hazardous targets require priority monitoring when necessary, and emergency monitoring becomes crucial when space events occur. China now ranks second in the world in the number of spacecraft in orbit and is transitioning from a major space power to a strong space power. However, due to insufficient overall coordination of space resources, various types of space data remain in a "who builds, who uses" model, with prominent sharing barriers. Infrastructure is not fully open and shared, and there is serious closed, low-level redundant construction. Social advantageous resources and forces have not yet fully participated in space development, and the enormous potential of the space economy is far from being released. At the same time, international cooperation is insufficient in breadth and depth, with equipment unevenly distributed globally and varying observation capabilities. Compared with the vast number of space debris, the number of dedicated space debris monitoring facilities is still small, and expanding the scale of the monitoring network and improving its capability to monitor small debris are the main directions of current space monitoring technology development.

Since the establishment of the U.S. SSN, researchers have studied sensor optimization problems to track a large number of resident space objects (RSOs) and maintain acceptable orbital state accuracy. Miller's work in 2007 was particularly notable, proposing marginal analysis based on the energy dissipation rate (EDR) of orbital targets to allocate scarce sensor resources to meet military accuracy requirements. Building on this, Hill et al. in 2010 used RSO state error covariance to more effectively schedule sensors, significantly improving target accuracy by reducing errors in catalogued states. Fisher and Herz transformed their research results into commercial software STK/Scheduler, which uses the Optwise algorithm to search for conflict-free, validated planning solutions and is widely used in the aerospace industry, though it has been embargoed for China since version 7.0.

In recent years, many scholars have conducted research on space target monitoring, planning, and scheduling problems, with related algorithms and software undergoing small-scale testing. Domestic scholar Jiang et al. simulated task scheduling scenarios for space debris monitoring radars, proposed a comprehensive fitness objective function based on scheduling score functions and equipment usage balance, and conducted numerical experiments using individual optimization and joint optimization particle swarm algorithms. However, for large-scale station networks, the practical significance of the balance function is questionable, and the paper only emphasized the iteration count advantage of the joint optimization algorithm without mentioning the solution time required. Zhang et al. constructed a mathematical model for monitoring resource optimization scheduling using specific constraints, designed a comprehensive fitness function based on seven evaluation indicators, and compared the solution time for thousand-level target numbers using particle swarm, neural network, grey wolf, genetic, and simulated annealing algorithms through encoding and parallel processing. Unfortunately, they did not specify the number of facilities or the computational environment, blurring the concepts of target count and task count. Internationally, the S5Lab research group, a collaboration between the Italian Space Agency (ASI) and the National Institute of Astrophysics (INAF), has deployed a network of observation stations dedicated to space debris observation and developed a scheduling program called NICO (Networked Instrument Coordinator for debris Observations). NICO uses genetic algorithms to resolve user request conflicts by defining user and observation target priorities, though it does not provide specific planning examples or results.

Different objective functions for monitoring task planning optimization require different methods. In reality, space debris moves at high speeds, exists in large quantities, and is distributed throughout Earth's space. Individual or small numbers of monitoring facilities in a network are constrained by monitoring capabilities (field of view size, detectable debris size, etc.), monitoring modes (tracking, scanning, or staring, etc.), and monitoring conditions (weather and equipment status). Therefore, the requirement to quickly plan tasks and complete predetermined monitoring using limited networked facilities is extremely urgent, yet previous research may struggle to meet such demands. For massive debris and multiple types of monitoring tasks, the characteristics of monitoring facilities and task requirements should be fully considered to maximize the overall effectiveness of the monitoring network. This paper argues that the primary task of a monitoring network is to collect sufficient orbit measurement data for routine debris cataloguing, while simultaneously conducting priority monitoring of important targets and new debris from space events. Therefore, basic task types include routine monitoring, important target monitoring, and new debris priority monitoring. This article aims to study the near-real-time scheduling optimization problem for massive space debris monitoring tasks by large-scale networks, making targeted improvements to classical linear/nonlinear programming methods to address the complex scenarios of space debris monitoring, ultimately enhancing debris monitoring and orbit cataloguing effectiveness.

2.1 Network Scheduling Optimization Problem

Given a monitoring network composed of multiple stations and a space debris population requiring monitoring, the scheduling process for debris monitoring tasks is shown in Figure 1 [Figure 1: see original paper], which includes resource allocation and task scheduling. Assume a monitoring network composed of n tracking-type facilities intends to observe M space debris objects. First, based on the position of each facility and the orbital information of space debris, observable arc information is calculated. Second, monitoring benefit is assigned to each measurable arc based on its importance. Finally, based on the spatiotemporal distribution of measurable arcs and monitoring benefits, the monitoring task optimization problem is solved, and observation task schedules for each facility are output.

Figure 2 [Figure 2: see original paper] shows the temporal distribution after obtaining information on 4 targets and 2 ground-based stations. Since a station (tracking facility) can only monitor one debris object within a time period, when a station has multiple measurable debris objects in the same time slot, it is necessary to select one. Considering the network of 2 stations as a whole, it is necessary to optimize its monitoring operations for the 4 debris objects. Table 1 lists the observable arc times and corresponding monitoring benefits for debris-station pairs, where the time unit (cid:28) represents the duration of an effective monitoring arc (or the minimum required monitoring arc). If a target can be monitored within the (cid:28) time period, its information can be recorded.

Assuming each station completes effective monitoring after monitoring a sub-arc of length (cid:28), it can immediately begin monitoring the next debris object. The task planning time is discretized into fixed-duration (cid:28) grids. Based on the gridded time and measurable debris information, a benefit list such as Table 2 can be obtained. The worker sequence is numbered according to station ID, where the concept of a "worker" will be formally introduced in Section 2.2. Annotated entries in the table indicate recorded observation arcs.

2.2 Mathematical Model for Network Scheduling Optimization

Based on the above scenario, the space debris task planning optimization for a monitoring network can be expressed by the following equations:

$$\text{Max } Z = \sum_{i,j} b_{ij} x_{ij}$$

$$x_{ij} = 1;\ \text{worker } i \text{ monitors debris } j \text{ (observable)}$$

$$x_{ij} \leq 1; \quad i = 1, 2, 3, \cdots, N;$$

$$x_{ij} \leq 1; \quad j = 1, 2, 3, \cdots, M;$$

where i is the monitoring task index after time discretization, referred to as a "worker," with a total of N workers equal to the product of the number of stations and the number of gridded time periods; M is the total number of debris objects; and *b_{ij}* is the information when worker i monitors debris j, determined jointly by the debris and the worker, reflecting both the importance of the debris and the station. The value *b_{ij}* can be comprehensively determined by the monitoring party (user) based on factors such as the distribution and data quality of recent monitoring arcs for the debris, required orbital accuracy, time since last observation, station geographic location, and equipment availability. When the monitoring object is a priority target, the user may require tracking whenever possible, in which case the monitoring benefit can be set to a very large value to ensure the target will definitely be monitored when visible. The specific determination method for *b_{ij}* will be adjusted based on debris cataloguing performance and equipment monitoring task execution effectiveness, which requires further research. Equation (3) ensures that one worker can only match one debris object for monitoring, while Equation (4) ensures that each debris object can be monitored at most once during that time period. For monitoring network task planning primarily aimed at debris cataloguing maintenance/expansion, it is first necessary to ensure that essential debris objects are monitored once within a certain time period (determined based on orbit accuracy requirements), while the specific timing and equipment for monitoring must comprehensively consider visibility and benefit (urgency). Under the constraints of Equations (3) and (4), the overall monitoring task benefit is maximized while ensuring completion of individual debris monitoring tasks. On the other hand, if a debris object can be monitored by multiple facilities simultaneously, aside from the designated facility, other idle facilities (with no assigned tasks) can monitor the debris object on their own or be assigned to do so without affecting the overall plan.

Equations (1)-(4) conform to the mathematical expression of the Linear Assignment Problem (LAP). The LAP has long been a focus of operations research and optimization, with solution methods 主要包括 primal-dual algorithms, simplex methods, and dual algorithms. Currently, mature algorithms commonly used in computers include the Hungarian algorithm by Kuhn and Munkres and the auction algorithm by Bertsekas and Orlin, as well as various optimization algorithms derived from them. Among these, the LAPJV algorithm (LAP solved by Jonker and Volgenant) is an efficient solution algorithm proposed based on the primal-dual algorithm combined with the shortest augmenting path algorithm.

2.3 Improvements to the LAPJV Algorithm

The LAPJV algorithm offers several advantages for the same problem scale: (1) it requires small memory allocation, has moderate code volume, and achieves high solution speed with fewer iterations; (2) it is applicable to both full-density and sparse matrices of different densities; and (3) it has low sensitivity to the values in the cost (or benefit) matrix B composed of *b_{ij}*.

However, in large-scale network scenarios, this algorithm faces three problems: (1) the total number of workers N and the total number of debris objects M are often different; (2) data is abundant, making storage costs still high; and (3) matrix sparsity is extremely high.

Considering these difficulties, this paper makes the following modifications to the model and LAPJV algorithm: (1) To obtain a square matrix representation of the cost matrix, virtual workers or virtual debris objects are introduced to expand the matrix, expressed as:

$$\text{Max } Z = \sum_{i,j} b_{ij}x_{ij} = B_{L\times L} \cdot X_{L\times L} = \begin{bmatrix} \cdots & \cdots & \cdots \\ \cdots & \cdots & x_{1L} \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & x_{LL} \end{bmatrix} \quad (L = \text{Max}\{M, N\})$$

(2) The square matrix form of the cost matrix creates many zero values, which further increases sparsity. All non-zero and zero elements can be efficiently stored by establishing a new mapping of *B_L×L*: first, invalid zero rows and columns, including those added due to Equation (5), are removed to reorganize the cost matrix, reducing sparsity and formally shrinking matrix dimensions; second, only non-zero effective sparse information is recorded as {*i; j; b_{ij}*}, while simultaneously recording the number of debris objects that each effective worker i can monitor to preserve zero element position information; finally, combining sparse information and position information enables equivalent implementation of row-wise or column-wise traversal operations on the original cost matrix in the LAPJV algorithm. The improved LAPJV (ILAPJV) algorithm can efficiently store and compute large non-square, high-sparsity matrices.

3.1 Limitations of the Linear Model and Improvements

In the linear assignment model, regardless of the position of the next debris object, the algorithm always selects the measurable debris that maximizes global benefit without considering the cost required to move the telescope from its current position to monitor that debris. As shown in Figure 3 [Figure 3: see original paper], after monitoring Debris 1, if the benefits of monitoring Debris 2 and Debris 3 are equal, the algorithm might select Debris 2 with lower telescope movement cost; if monitoring Debris 3 offers higher benefit but also higher telescope movement time cost, the monitoring benefit and telescope movement time cost should be comprehensively considered. In reality, each current choice affects subsequent choices, creating a conflict between local and global optimization.

Let *C_{ij}* denote the cost of moving the telescope (worker i) to the position to monitor debris j. This cost depends on the current telescope position and the target debris position, expressed by *d_i(j; k)*, the angular distance between debris k (just monitored) and debris j. The telescope movement cost is given by:

$$C_{ij} = c \cdot x_{i-1,k} \cdot d_i(j;k)$$

where c is the unit cost of moving the telescope (time cost required to move the telescope by 0.1 radians). With current servo capabilities, the time cost for long-distance versus short-distance movement of ground-based telescopes is not linear but relatively similar; however, to maintain satellite attitude stability, the movement time of space-based telescopes is essentially linear with distance. Whether for ground-based or space-based tracking, telescope movement cost is a factor worth considering. The specific determination method for telescope movement cost and its impact on monitoring task planning are issues for future research. Generally, cost values need to match benefit values.

3.2 Nonlinear Model and Comparison with TSP

Combining Equation (6) with Equation (1) and comprehensively considering monitoring benefit and telescope movement cost, the task scheduling optimization objective function becomes:

$$\text{Max } Z' = \text{Benefit}-\text{Cost} = \sum_{i,j} \left(b_{ij} - c \cdot x_{i-1,k} \cdot d_i(j;k)\right) x_{ij} \quad (\text{when } i = 1, c = 0)$$

The remaining constraints are the same as Equations (2)-(4). This nonlinear problem is similar to the Traveling Salesman Problem (TSP) proposed by Dantzig et al. The TSP is generally described as finding the shortest route (journey) for a salesman starting from a given city, visiting each city in a specified group, and returning to the original starting point.

The TSP optimal solution problem has been proven to be NP-Hard with exponential time complexity O(n!). Current TSP solutions mainly follow two directions: one is exact optimization algorithms that are time-consuming but precise; the other is heuristic algorithms, including bio-inspired ant colony algorithms, genetic algorithms, particle swarm algorithms, and local search k-opt algorithms. If minor deviations are acceptable, heuristic algorithms can obtain good local optimal solutions in relatively short time, with results very close to global optimal solutions.

As shown in Figure 4 [Figure 4: see original paper], the nonlinear model considering movement cost differs from TSP in the following ways: (1) debris and stations are heterogeneous, making it impossible to directly establish a distance square matrix, which may require expansion into an extremely high-dimensional square matrix, and due to the heterogeneity of debris and stations, effective observation data would be very sparse if converted to a square matrix; (2) not all stations have observable debris, and it is necessary to verify whether debris has been uniquely observed; (3) the solution path is not a closed loop.

Considering these issues and after small-scale testing, the authors believe that bio-inspired intelligent algorithms are not suitable, while k-opt algorithms can better solve TSP problems.

3.3 Improvements to the k-opt Algorithm

The k-opt algorithm, also known as the k-exchange algorithm, operates on a randomly initialized circuit by continuously replacing k link connections under the action of sequential exchange criteria, feasibility criteria, positive benefit criteria, and disjoint criteria until it can no longer produce a shorter path length. Larger k values increase the likelihood that the final solution is optimal.

However, the time complexity of the k-opt algorithm is O(n^k). Research shows that the 2-opt algorithm is very effective for searching and solving TSP problems. This paper will explore the performance differences between 2-opt and 3-opt algorithms in experiments. To make k-opt more suitable for solving the nonlinear model, four modifications are made: (1) perform local exchanges based on the main idea of the k-exchange algorithm but not strictly following its solution process; (2) use a greedy algorithm (GA) to select for each worker the debris with maximum benefit and no conflicts, then subtract telescope movement cost to generate an initial solution; (3) use sparse matrix recording to record effective observation information, sorting all measurable arcs under the same worker by benefit before searching; (4) when attempting to exchange in new debris, use a special checking function to accelerate convergence, ensuring unique matching between workers and debris, allowing the algorithm to only try the most promising worker-debris combinations. For example, if a high-benefit debris has been attempted and failed, another low-benefit debris will not be attempted.

4.1 Performance Comparison of ILAPJV and k-opt (k=2,3) Algorithms

To test the performance of the ILAPJV algorithm versus k-opt (k=2,3) algorithms under large data volumes, two task scheduling optimization experiments were designed. In the first experiment, orbital parameters for 1,000 space debris objects and 4 stations were given, resulting in 46,000 observable arcs within 3 days, with each arc's monitoring benefit being a number between 2 and 32. In the second experiment, orbital parameters for 5,000 space debris objects and

4 stations were given, resulting in 220,000 observable arcs within 3 days, with each arc's monitoring benefit being a number between 0 and 800. The effective monitoring arc length was set to 4 minutes. In debris visibility analysis, certain equipment can continuously monitor a single target for up to 50 minutes; however, from an orbit cataloguing perspective, only 4 minutes of monitoring is needed. If the target is a priority target, continuous monitoring can be achieved by setting an extremely high benefit. The experimental environment was an Intel(R) Core(TM) i5-10400F CPU @ 2.90GHz.

Monitoring task planning was performed for 120, 240, and 480 minutes. Algorithm performance metrics included task scheduling optimization solution time, total benefit, and accuracy, where accuracy was defined as the ratio of task benefit planned by an algorithm to that planned by the ILAPJV algorithm, expressed as a percentage. In the first experiment, the performance metrics of ILAPJV, 2-opt, and 3-opt algorithms for solving the linear model were compared, as shown in Table 3 . Table 4 shows the results of the second experiment.

Table 3 Performance comparison of optimization algorithms in Experiment 1

Algorithm	Solution Time (s)	Total Benefit	Accuracy (%)
ILAPJV	0.006	-	100
2-opt	-	-	-
3-opt	-	-	-

Note: 120, 240, 480 indicate planning monitoring duration in minutes.

Table 4 Performance comparison of optimization algorithms in Experiment 2

Algorithm	Solution Time (s)	Total Benefit	Accuracy (%)
ILAPJV	0.053	-	100
2-opt	-	-	-
3-opt	-	-	-

Note: 120, 240, 480 indicate planning monitoring duration in minutes.

From Tables 3 and 4, we can see: (1) The ILAPJV algorithm demonstrates excellent performance in both experiments, offering good solution efficiency for large-scale problems with minimal impact from the magnitude of benefit values *b_{ij}* on solution time. (2) Both 2-opt and 3-opt algorithms show remarkable performance, with solution accuracy above 99% in both experiments. In Experiment 2, the 2-opt algorithm required less time than ILAPJV to solve the optimization problem, with accuracy close to or better than 99.9%. When using the 3-opt algorithm, its accuracy is slightly higher than 2-opt, but as problem scale increases, its solution time cost becomes difficult to ignore—the 240-minute task planning requires solution time hundreds of times longer than the 2-opt algorithm. (3) The GA has the highest solution efficiency but unsatisfactory accuracy.

Based on these three points, ILAPJV can efficiently solve linear optimization problems; although 3-opt yields more precise results, its high solution time cost makes it unsuitable for real-time task planning optimization. Therefore, the 2-opt algorithm, which balances accuracy and speed, is adopted to solve the nonlinear optimization problem involving telescope movement cost.

Taking the 120-minute task planning in Experiment 2 as an example, with 4 stations and 5,000 space debris objects, the linear model and nonlinear model with unit cost $c = 10$ and $c = 50$ can monitor 120 debris objects, while $c = 100$ can monitor 117 debris objects, indicating that movement cost affects the number of debris monitored. Considering each monitoring arc is 4 minutes long, each station can monitor at most 30 debris objects within 120 minutes, and 4 stations can monitor at most 120 debris objects, thus monitoring equipment is fully utilized. Moreover, the planned monitoring benefit is maximized. As shown in Figure 5 [Figure 5: see original paper], $c = 0$ represents the total number of debris monitored after solving the linear model with ILAPJV, while $c \neq 0$ represents the total number of debris monitored after solving the nonlinear model with 2-opt.

4.2 Network Station Deployment and Space Debris Selection

When forming a space debris monitoring network, we selected 7,170 space debris objects from the NORAD catalogue. Their "true orbits" were generated using the catalogue orbit improvement method based on TLE data proposed by Chen Junyu et al. Visibility analysis was performed using the effectiveness software developed by the Wuhan University Space Situational Awareness team to set up ground stations and analyze debris visibility. The monitoring network consists of 200 ground stations distributed globally, with station locations selected from SNX files published by the International GNSS Service (IGS), as shown in Figure 6 [Figure 6: see original paper].

Table 5 Station equipment parameters

Equipment Type	Detection Sensitivity	Effective Monitoring Arc Length	Lens Movement Cost
Ground-based tracking telescope	20 mag	0°-360°	0°-90°

Each station is assumed to be equipped with a ground-based tracking telescope with specific parameters shown in Table 5. Figure 7 [Figure 7: see original paper] illustrates the method used by the effectiveness software to generate simulated observation arcs: after inputting basic parameters such as the target's precise orbit, station location and equipment information, and simulation start/end times, the target orbit is interpolated according to a set step size; at each interpolation moment, the positions of the target and station in the inertial frame are calculated, and target visibility is determined based on the observation station's range; if the target is visible relative to the station, observation values are calculated to generate measurement arcs.

4.3 Global Network Monitoring Simulation Results

Using the above ground network to monitor debris, the monitoring operation period was March 7-9, 2021. Each debris object's monitoring benefit was set as a random number between 0 and 100. The effective monitoring arc length was set to 60 seconds, based on requirements for orbit updating of catalogued targets and initial orbit determination/arc association algorithms for new targets. A 4-hour monitoring task optimization was performed (square matrix B_{48,000$\times$48,000}), with the constraint that the same equipment can continuously monitor the same target for a maximum of 180 seconds per pass, after which observation stops even if the target remains visible. The required computation time and monitoring benefits are shown in Table 6 .

Table 6 Simulation results for 4-hour planning tasks (algorithm, cost)

Algorithm, Cost	Computation Time (s)	Total Benefit	Monitoring Debris Ratio (%) (Monitored/Total)
ILAPJV, c=0	12.051	289,399.07	40.88 (2,931/7,170)
2-opt, c=1	162.071	285,333.79	40.70 (2,918/7,170)
2-opt, c=10	164.026	-	-
2-opt, c=50	-	-	-

The results show: (1) Using the ILAPJV algorithm to solve the linear problem (without considering telescope movement cost) took 12.051 seconds, demonstrating high solution efficiency; (2) Setting telescope movement cost at $c = 10$ per radian, using 2-opt to solve the nonlinear problem took 164.026 seconds, which can be controlled within 3 minutes; (3) In the 4-hour observation plan, the nonlinear model monitored 2,918 debris objects once, while the linear model monitored 2,931 debris objects once, both accounting for over 40% of all debris.

Debris visibility analysis shows that among the 200 stations, only 158 have visible debris to observe, affecting overall equipment utilization. When the grid time is 1 minute, equipment utilization appears low. Therefore, we set the grid time to 3 minutes for task planning. Using both nonlinear and linear models, 2,918 and 2,931 debris objects can still be observed, respectively, with equipment time utilization essentially triple that of the 1-minute case. Considering that this experiment has 200 stations but only over 7,000 debris objects, monitoring resources are relatively abundant, and we planned tasks based on the basic monitoring requirement of observing each debris object only once. Combining these factors, the proposed algorithm effectively completes monitoring task planning with cataloguing maintenance as the primary goal. On the other hand, when monitoring resources are abundant, idle equipment can conduct monitoring operations on their own or be assigned to do so, clearly improving equipment utilization without affecting the overall plan. It can be envisioned that when equipment resources are relatively scarce compared to debris quantity, equipment utilization will be higher. In fact, due to the near-real-time planning capability of this algorithm, when debris monitoring task completion changes, new planning can be performed promptly. Finally, based on the result that 40% of debris was observed within 4 hours, if these debris do not need to be monitored again in the short term, all debris could be observed once within 10 hours, thus better achieving the goal of catalogue maintenance.

The above algorithm test results demonstrate that the 2-opt algorithm can be used for near-real-time monitoring task planning optimization in large-scale networks.

5 Conclusion

Addressing the scheduling optimization problem for space debris network monitoring tasks in multi-task scenarios, we established both a linear model that does not consider telescope movement cost and a nonlinear model that does, with the latter more realistically describing actual monitoring problems. Based on analysis of linear problem characteristics, we improved the LAPJV algorithm to achieve fast and accurate global optimal solutions. For the nonlinear model, using the improved 2-opt algorithm enables efficient solution of local optimal solutions with good consistency with global optimal solutions. Both models have significant practical meaning. Algorithm performance test results show that the two improved algorithms can solve problems with abundant data but scarce actual effective observation values, offering high solution accuracy and efficiency suitable for near-real-time monitoring task planning in large-scale networks.

Although massive space debris cannot be cleared in the short term, on one hand, monitoring equipment originally for space weather monitoring and research is gradually expanding into the space debris domain. China's space-ground integrated space target monitoring system is being actively constructed, with monitoring networks growing increasingly large globally and international cooperation trends emerging. On the other hand, frequent debris events and space hotspot activities are making space monitoring tasks more complex and diverse, demanding higher timeliness and making overall network effectiveness optimization an important technical means. In this context, the linear and nonlinear planning models and solution algorithms based on multi-task scenarios can provide an effective solution for near-real-time scheduling requirements.

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Note: Figure translations are in progress. See original paper for figures.