Operations Research applications in the subject of Space debris monitoring/removal

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1 Introduction

The problem of space debris has gained increasing attention in recent decades as the density of objects in low Earth orbit (LEO) continues to rise. This debris, which includes defunct satellites, rocket upper stages, and fragments from collisions, poses a serious hazard to operational spacecraft. Without active intervention, the space environment may reach a critical density threshold known as the Kessler syndrome, where debris collisions generate further debris in a cascading feedback loop.

Active Debris Removal (ADR) is a widely studied approach to reduce the risk of future collisions by selectively removing high-risk objects from orbit. However, due to the high cost, complexity, and limited onboard resources of ADR missions, effective planning and optimization are essential. Recent literature has explored a variety of optimization-based approaches to ADR mission planning. These include mixed-integer models using time-expanded networks [5], trajectory optimization via mixed-integer nonlinear programming [3], and even machine learning-based planning strategies [6]. These works typically address realistic mission environments involving dynamic orbital mechanics, complex transfer constraints, and time-varying objectives.

In this project, we build upon the ideas presented in this body of work but formulate a simplified and tractable variant of the ADR planning problem. Our model assumes a static, two-dimensional orbital plane in which all debris are fixed in perfectly circular orbit. The objective is to determine the optimal sequence of debris to remove using a mothership spacecraft equipped with a limited number of drones and a finite fuel budget. Each drone is capable of independently deorbiting one piece of debris upon deployment, requiring the mothership only to reach the debris orbit. As a result, transfer costs are modeled using idealized Keplerian ΔV estimations without considering time or perturbations.

The problem is formulated as a Mixed Integer Linear Program (MILP), which jointly optimizes the selection and ordering of debris targets, subject to resource constraints on fuel and drone availability. While this formulation abstracts away many of the complexities of real-world ADR, it allows for a focused study of combinatorial aspects of mission planning. Inspired by prior work such as [5, 4, 1], we also propose a matheuristic to solve larger problem instances efficiently.

2 Description of the Problem and Simplifications

The accumulation of artificial space debris in Earth orbit is a growing concern for satellite operators, space agencies, and the sustainability of near-Earth space. As more objects are launched into orbit—ranging from communication satellites to scientific payloads and megaconstellations—the probability of collisions with defunct spacecraft, rocket stages, and fragmentation debris continues to rise. Each collision can generate thousands of new fragments, amplifying the risk of further incidents in a self-perpetuating cycle known as the Kessler syndrome.

To prevent this scenario, various strategies have been proposed, including mitigation techniques (such as mandatory deorbiting at end-of-life) and active debris removal (ADR) missions. ADR aims to physically remove high-risk debris from orbit, typically by capturing or redirecting it into the Earth's atmosphere where it burns up. While conceptually straightforward, ADR poses significant planning and operational challenges.

From an operations research perspective, the ADR problem can be viewed as a complex resource-constrained routing and scheduling task. The key challenges include:

- **Target Selection:** With thousands of debris objects in orbit, selecting a subset for removal that maximizes risk reduction or mission value is nontrivial.
- **Sequence Optimization:** The order in which targets are visited affects both the fuel consumption and feasibility of the mission, particularly due to orbital mechanics constraints.
- **Resource Constraints:** ADR spacecraft typically have limited fuel, time, and payload capacity, making efficient use of resources critical.
- **Trajectory Planning:** Computing the optimal orbital transfers between debris is computationally expensive and depends on nonlinear and time-varying dynamics.
- **Scalability:** Even simplified formulations of the problem can quickly become intractable as the number of debris or mission constraints increase.

Addressing these challenges requires a balance between physical realism and computational tractability. Optimization methods such as Mixed Integer Linear Programming (MILP), heuristics, and hybrid "matheuristics" have been explored to enable practical mission planning. In the simplified version considered in this work, we abstract away some of the complexities of orbital dynamics in order to focus on the core combinatorial structure of ADR planning. Such simplifications are as follows:

- **The system is static:** We assume that the whole orbit represents one debris this way the spacecraft only needs to reach the designated orbit for it to deorbit the debris.

- **Single plane problem:** The problem is simplified to be in a singular plane, allowing for more simple transfer calculations disregarding change of plane fuel costs.

- **Idealized Keplerian orbits:** The assumption that all the orbits of the debris are perfectly circular. This allows for simpler calculations to be made for ΔV required to transfer between orbits.

- **Time is disregarded:** Time and transfer windows are disregarded with an assumption that the spacecraft can operate indefinitely, meaning time constraints are not a problem for it and there is no need to model them.

- **The space ship is a drone-ship[3]:** It is assumed that the spaceship is a drone-ship only needing to transfer to the debris orbit and release a drone that will do the deorbiting work for it. This allows us to disregard the ΔV required to deorbit the debris and get back to the same velocity with one spacecraft while introducing a new constraint variable that is the amount of drones available on the ship.

These assumptions significantly reduce the computational complexity of the problem while preserving the essential features of target selection, transfer cost evaluation, and resource allocation. This abstraction enables a focused investigation into the core decision-making structure of ADR mission planning, and serves as a foundation for testing exact and heuristic optimization methods within a controlled and interpretable setting.

3 Description of mathematical and matheuristics model and implementation

Our mathematical model written in AMPL used all the simplifications from the previews chapter. So, our model is a very simplified general version of the models described in scientific papers. This means that our model only has 8 constrains which is significantly less than proper accurate models (which can have tens of thousands constrains [2] if the model is dynamic). In our case, main constraints ensure that our spacecraft has enough fuel for each transfer, will not visit already de-orbited debris, and will not de-orbit more debris than drones. Also, our models take into account that losing the drone changes the spacecraft mass which increases Δv of it. In our case, the data set used to test model was generated manually and are shown below.

Table 1: Generated space debris parameters.

Id	Orbit height (km)	Reward
D1	7300	10
D2	7000	7
D3	7200	8
D4	7300	2
D5	7100	6
D6	6900	8
D7	6900	4
D8	7100	10
D9	7200	3
D10	6800	5

Table 2: Generated spacecraft (s/c) parameters.

Parameter	value
Initial s/c mass	2000 kg
Count of de-orbiting drones	4
Count of de-orbiting drones	100 kg
Specific impulse	350 s
Available fuel	800 kg
Initial s/c orbit	7400 km

For matheuristics model we decided to use greedy algorithm in a two-step process.

The first is to apply a greedy algorithm to obtain the initial solution. After that, we make local MILP improvements. This means we let program to unfix some variables and test with greedy algorithm to see if a better solution could be reached. This algorithm was implemented using *Python* and *amplpy* library to incorporate a mathematical model in the matheuristics model.

4 Results

From our case study mathematical model we get that the maximum reward is 36. This is obtained from the deorbiting D1, D3, D6 and D8 debris. The order was as follows: Initial orbit -¿ D3 -¿ D6 -¿ D1 -¿ D8. These results match the ones got from matheuristics model.

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