Impact of Policy on the Establishment of the LEO-based Collection-As-A-Service Concept

Madeline Bowne* and Tristan Sarton du Jonchay †
Aerospace Systems Design Lab, Georgia Institute of Technology, Atlanta, GA 30332

Dimitri Mavris‡
Aerospace Systems Design Lab, Georgia Institute of Technology, Atlanta, GA 30332

As low Earth orbit (LEO) gets increasingly congested with mega-constellations and researchers learn more about the environmental impact associated with launching and de-orbiting single-use satellites, there's growing interest in fostering circular economies in space. While In-Space Servicing, Assembly, and Manufacturing (ISAM) is a critical capability for circular space economies, ISAM in LEO has made very little traction, even though the LEO environment could benefit from improved circularity. While advancements in technology and improved concepts of operations (CONOPs) could help incentivize the private sector to pursue ISAM in LEO, government intervention may be necessary. Since mega-constellations provide critical services, future regulations and policies aimed at mitigating environmental impact should strike the balance between supporting the continued growth of the space industry and encouraging sustainable operations. This paper aims to identify combinations of policy, strategy, and CONOPs that sufficiently incentivize the private sector to improve sustainability in LEO. This research, featuring collection-as-a-service (CAAS) CONOPs to improve the case for ISAM in LEO, leverages a framework that allows the satellite constellation operator and ISAM infrastructure to incrementally adapt to highly uncertain future scenarios.

I. Nomenclature

ADR	=	Active Debris Removal
$ENPV$	=	Expected Net Present Value
GEO	=	Geosynchronous Orbit
$ISAM$	=	In-Space Servicing, Assembly, and Manufacturing
LEO	=	Low Earth Orbit
NPV	=	Net Present Value
OOS	=	On-Orbit Servicing
$VARG$	=	Value at Risk/Gain

II. Introduction

A distinct property of the space industry is its operation through multiple environmental regimes and consequently, its impact on multiple environmental regimes. As launch frequency increases and satellite constellations grow, the space industry has begun to reflect on its environmental footprint on Earth, in orbit, and in the atmosphere. The space sustainability conversation has gained traction in recent years, with spacecraft operators, academics, and policy-makers alike reflecting on the future needs of the space industry. The majority of space sustainability research focuses on orbital congestion, but a growing contingent is investigating the industry's impact on atmospheric pollution and degradation as the launch rate increases and more and more spacecraft burn up in the atmosphere [1] [2] [3]. Researchers have also become aware that climate change alters the composition of the upper atmosphere, which could have repercussions for de-orbiting operations that rely on atmospheric drag [4]. Circular space economies that enable reusable satellites and

*Graduate Researcher, ASDL, School of Aerospace Engineering, Georgia Tech
†Research Engineer, ASDL, School of Aerospace Engineering, Georgia Tech
‡S.P. Langley Distinguished Regents Professor and Director of ASDL, Georgia Tech, AIAA Fellow

support active debris removal infrastructures could provide a solution to these problems and mitigate environmental uncertainty, but there is little interest in LEO-based ISAM/OOS, a critical capability for circular space systems. The key to improved circularity is likely a combination of improved CONOPs, strategy, and policy to motivate the private sector to invest in OOS for satellites in Low Earth Orbit. A framework that compares system performance and includes collaboration of CONOPs, strategy, and policy, accounting for the highly uncertain space environment, could provide the means of path-finding a more sustainable future in space.

Several researchers have proposed methods to improve OOS CONOPs in LEO, such as collaborative maneuvering [5] [6], proliferated servicing pods [7], and leveraging J2 for more efficient maneuvering [8] [9]. These offer improvements compared to the classic OOS CONOPs intended for satellites in GEO. However, to properly incentivize satellite constellation operators, OOS must address their fundamental needs: lowering costs and maintaining consistent coverage. The presence of deep uncertainty is of critical concern for space operations, making the study of flexibility crucial to mitigating risks and maximizing opportunities. The business case for OOS in LEO should be engineered to ensure the constellation operators avoid undue risk and seize opportunity for future growth. Previous flexibility frameworks demonstrate the value of flexibility that OOS offers to satellite operators [10] [11] [12]. However, these frameworks do not include multiple sources of uncertainty or consider the combination of multiple flexible options and policy impacts. A novel concept for OOS in LEO, collection-as-a-service (CAAS), as introduced by Bowne et. al at SciTech 2025 [13], provides a flexibility mechanism that builds upon the Jakob et. al. proposal for multi-echelon sparing for satellite constellations in LEO [14]. The Bowne et. al. flexibility framework shows how a combination of better CONOPs and strategy could reduce constellation emissions while keeping costs close to that of a baseline system that uses no spare warehouses or CAAS.

In addition to improving CONOPs and strategy, policy offers another method for influencing commercial activity. There are several proposals for policies aimed at reducing orbital congestion, but few aimed at reducing atmospheric degradation. The U.S. Government Accountability Office (GAO) highlighted atmospheric emissions from large satellite constellations as an environmental concern, but noted that the limited state of research prevents policy development [15]. Recent appeals to include the space environment under NEPA have not succeeded, as the FCC and courts have deemed space a non-human environment [16].

Orbital congestion mitigation and atmospheric pollution reduction have much in common, even though they address different regimes. While there is limited research on policies and strategies that could reduce atmospheric pollution associated with space operations, much can be borrowed from policy recommendations on orbital congestion. Proposed incentives for responsible space use include orbital use fees, collision charges, mandatory insurance, and a deposit/refund system. For instance, Adilov et al. propose a Pigouvian tax that includes a launch tax and debris mitigation fee to fund debris removal [17]. Rao et al. recommend orbital use fees (OUFs), estimating an optimal fee of \$14,900 per satellite, increasing to \$235,000 by 2040 to offset collision costs not fully accounted for by satellite operators [18]. Roy et. al. study the feasibility of subsizing on-orbit recycling with proceeds from orbital use fees [19]. Assuming the international community would agree to an OUF, they study the impact on operator decision-making by running a sensitivity study of OUF values in a system dynamics model. They found that high OUFs shortened break-even time for on-orbit recycling, but that profits were more sensitive to space activity-level than the OUF policies [19].

Macauley suggests a deposit/refund system, with rebates for net environmental contributions [20]. Mandatory on-orbit insurance and absolute third-party liability is another option for promoting sustainable operations [21]. Despite the number of policy proposals, there is little research on how to surgically apply government intervention in a manner that collaborates with CONOPs and strategies aimed at improving the case for OOS in LEO. Ideally, policy should help "tip the scales" on a viable business case where needed, supporting improvements in constellation sustainability while limiting the penalty on the satellite operator and the costs on the taxpayer.

Fundamentally, government intervention impacts the costs and benefits of the various options available to constellation operators. It is worthwhile to consider how different policies, fines, or regulations could promote early adaption of sustainable infrastructure that pay off in the future. This paper extends the initial Bowne et. al. framework by applying parametric rewards and penalties to assess the costs and benefits of ISAM for satellite constellation operators, exploring which combinations of rewards and penalties best support a viable business case across a series of uncertain scenarios. In doing so, this paper contributes a methodology for developing public-private partnerships that create conducive cases for sustainable space operators through a variety of possible futures. The results lay the groundwork for a deeper conversation on which policies reinforce the feasibility of ISAM in LEO. The following section provides background on the CONOPs and framework presented by Bowne et. al. and details recent adjustments and refinements. Section IV provides the methodology for incorporating policy within the framework. Lastly, Section V describes the results and analysis of the experimentation.

III. Background

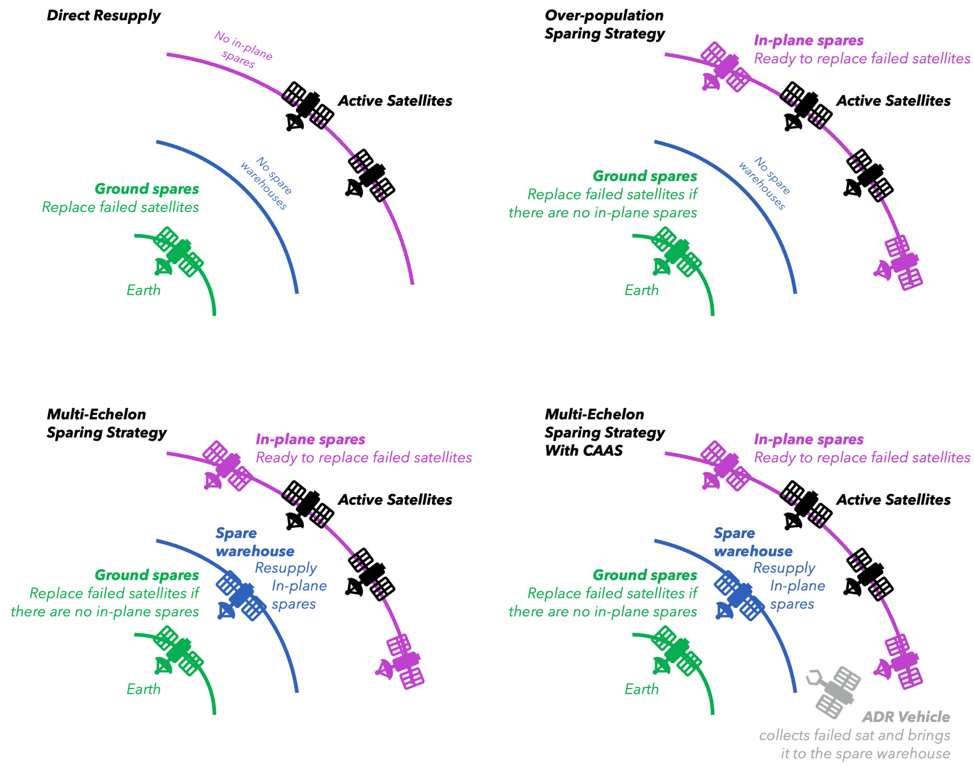


Fig. 1 Satellite Constellation Sparing Strategies

When designing an orbital servicing infrastructure to support satellite constellations, it is critical to consider the priorities and needs of satellite operators. In addition to reducing costs and avoiding collisions, operators need to maintain consistent coverage. When satellites fail and the operator needs a replacement, they have a number of sparing options, shown in Fig. 1. The first option is to launch a replacement satellite directly from Earth, but this comes with launch delays and higher launch costs. A common strategy is over-population, where the operator places more satellites than they need in orbit so the spares can respond quickly in the event of failure. This method reduces the need for direct launches of single satellites, but can still pose challenges if no in-plane spares remain and a failure occurs before the next batch launch.

The multi-echelon sparing strategy, proposed by Jakob et. al., builds upon the overpopulation method and adds orbital spare warehouses that take advantage of batch launch rates [14]. In their study, Jakob et. al. determine that placing spare warehouses in lower parking orbits that slowly replenish in-plane spares as they change RAAN via J2 perturbation is a cost-effective and timely way of replenishing constellations after satellite failures.

The CAAS CONOPs, proposed by Bowne et. al., takes the multi-echelon sparing strategy another step forward for mega-constellations in LEO [13]. Bowne et. al. introduce ADR vehicles that can collect old satellites and bring them back to the spare warehouses, where they can be serviced, de-orbited, or returned to Earth depending on existing capabilities and the state of uncertainty. As warehouses grow their collection of old satellites, they have a number of options available, as illustrated in Fig. 2. The preliminary findings from Bowne et. al.'s paper suggested that spare warehouses that collect old satellites have the potential to reduce emissions from launching and de-orbiting spacecraft without significantly increasing costs.

Previously, Bowne et. al. present CAAS CONOPs where the ADR vehicles are either launched with a warehouse or are sent to a warehouse along with a resupply mission if the customer opts to add another vehicle. Additionally, the previous version of the CAAS CONOPs only sends out ADR missions from the warehouses. In this paper, however, the customer has the option of launching ADR missions directly from Earth. Another adjustment to the CONOPs in this paper is that rather than charge a fine for every satellite failure, the satellite constellation operator is compelled to use

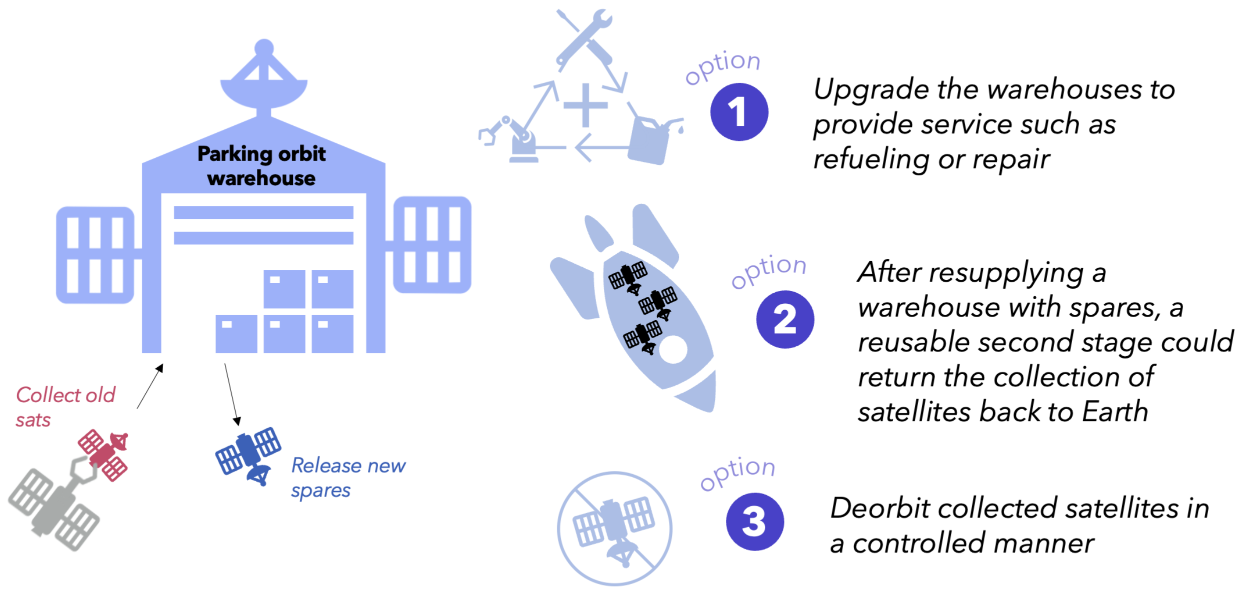


Fig. 2 Collection Hub Options

ADR of some form for every failed satellite in order to reduce collision risk in the orbital environment and secure their FCC authorization for a replacement satellite. ADR vehicles that are launched from Earth have the option of docking with a nearby warehouse or they can de-orbit itself and its collection of satellites. Consequently, the warehouses can grow their employ of ADR vehicles in an incremental fashion. Aside from these adjustments, the CAAS CONOPs remain the same. To measure the performance of the spare/collection warehouse concept, this paper compares it with a baseline CONOPs with no warehouses and ADR missions launched exclusively from Earth, called the 0-warehouse baseline, shown in Fig. 3.

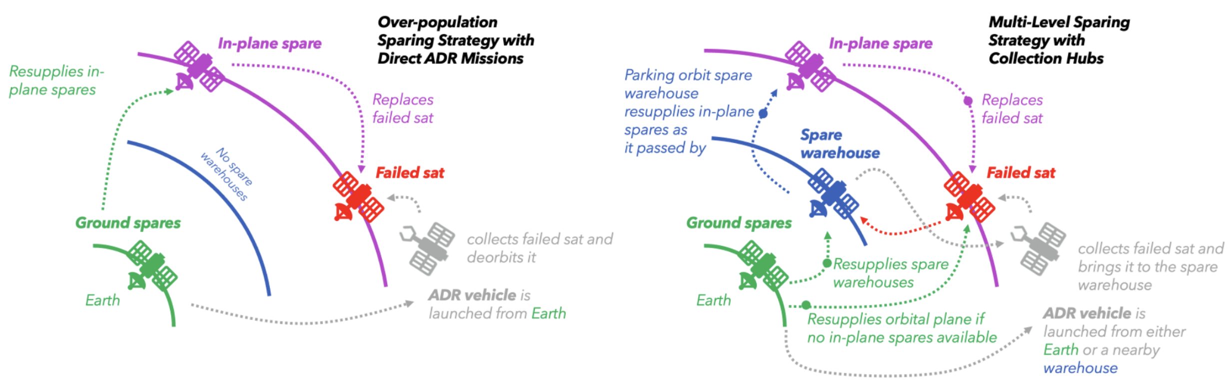


Fig. 3 Overpopulation (left) vs. Multi-Level with Collection (right)

The Bowne et. al. flexibility framework draws inspiration from earlier OOS flexibility frameworks [10] [11] [12], but uses a discrete-event simulation approach paired with decision rules and Monte Carlo scenarios. These framework properties accommodate multi-level flexibility, a large design space, multiple sources of uncertainty, and the ability to study the combinatorial effect of options. The Bowne et. al. flexibility framework shares many elements with Lin et. al.'s flexibility framework for offshore oil infrastructure, which screens options for multi-level flexibilities by employing an integrated systems model and implementing flexible options when specific conditions trigger decision rules [22]. This framework does not attempt to predict the future; rather, it aims to explore a broad range of plausible futures that enable comparisons of robustness and relative performance between different CONOPs and flexible options. A summary of all uncertain variables, how they're modeled, and their parameters, can be found in the Appendix, in Table 8. Initial cost assumptions for technologies and services are derived from best-available data or best-guess estimates, often triangulated from multiple sources due to limited publicly available information. These estimates, located in Table 9 in the Appendix, serve as a baseline for demonstrating the proposed framework. Table 10 in the Appendix delineates all the cost sources in this simulation. Future work incorporating higher-fidelity cost models may yield results with greater accuracy and confidence.

IV. Methodology

A. Discrete Event Simulation

This paper builds on the DES and flexibility framework developed by Bowne et al. [13], with several modifications to account for failure risk categorization, regulatory pressures, and economic decision-making by satellite operators. While the previous paper regarded the constellation operator and servicing-infrastructure provider as separate entities, this paper simplifies the cost models by assuming that the satellite constellation operator also owns and manages the warehouses. These adjustments allow for more straight-forward yet realistic interactions between constellation operators and policymakers under evolving technological and regulatory conditions. By incorporating operational failure typologies, and improved decision rules, this framework provides a more nuanced representation of how servicing infrastructure might co-evolve with the growing demands of orbital congestion and satellite sustainability.

1. Failure Typology and ADR Demand

This framework also models operational uncertainties, particularly regarding collision risks from satellite failures. Previously, the simulation did not differentiate between satellite failure types. In this paper, however, some failures render satellites completely inoperable. The constellation operators must obtain new FCC authorization for replacement satellites. The FCC reviews each application with consideration for the cumulative collision risk posed by the constellation, potentially affecting authorization decisions for replacement satellites if a nearby inoperable satellite poses a risk [23][24]. Constellation operators, such as OneWeb, are engaging in public-private partnerships to remove failed satellites with Astroscale [25]. ADR services serve as a form of insurance for constellation operators, preventing collision-related expenses that could far exceed the cost of the ADR mission itself. For these reasons, this framework assumes that all failed satellites receive ADR, and that 50% of failed satellites experience a delay in their replacement authorization until the failed satellite is removed. ADR mission cost and the indirect cost associated with coverage loss are accounted for in the customer's total cost.

2. Collision Risk and Cost Modeling

While a collision event could cost an operator millions in damages, collision avoidance maneuvers themselves also impose financial burdens. To capture these risks, this framework also adds a simple collision model. It uses an exponential cost function that increases with the scenario's time step (reflecting growing orbital congestion), the number of non-maneuverable satellites, and their time spent in orbit.

3. Adaptive Decision-Making Framework

To simulate the response of the satellite operator to the state of the uncertain environment, this simulation improves upon previous iterations of the decision rules, guiding if and when the operator opts to launch a new warehouse, upgrade a warehouse, or upgrade new satellites to be refuelable or repairable in space.

The decision to upgrade satellites to be refuelable or repairable comes from periodic economic assessments that compare the benefits of refurbishment with the cost to upgrade using Monte Carlo trials and discounted cash flow analysis. A parametric multiplier allows the user to incorporate risk preferences. If the projected satellite collection rate exceeds a break-even threshold, the upgrade is triggered, at which point the percentage of new satellites that are upgraded is contingent on the rate of collection, with at least half of all new satellites receiving the upgrade.

Decision analysis for new warehouses also occurs periodically, based on the costs and revenue of avoided penalties, savings, and rebates, balanced against infrastructure costs and learning curves. Warehouse upgrade decisions are made based on projected service revenues or fleet composition, ensuring that the servicing infrastructure evolves in tandem with the constellation. These decision rules include the costs and savings associated with various forms of government intervention, as described in the following section.

B. Policy Modeling

While there are a number of policies that could influence the market for OOS in LEO, this paper focuses on five different policy schemes: Orbital Use Fees (OUFs) with either refunds or subsidies, contingent fines, mandatory insurance, and taxes that help subsidize sustainable infrastructure. This section elaborates on the schemes included within this paper, illustrated in Fig. 4, and describes their impact on decision logic within the simulation.

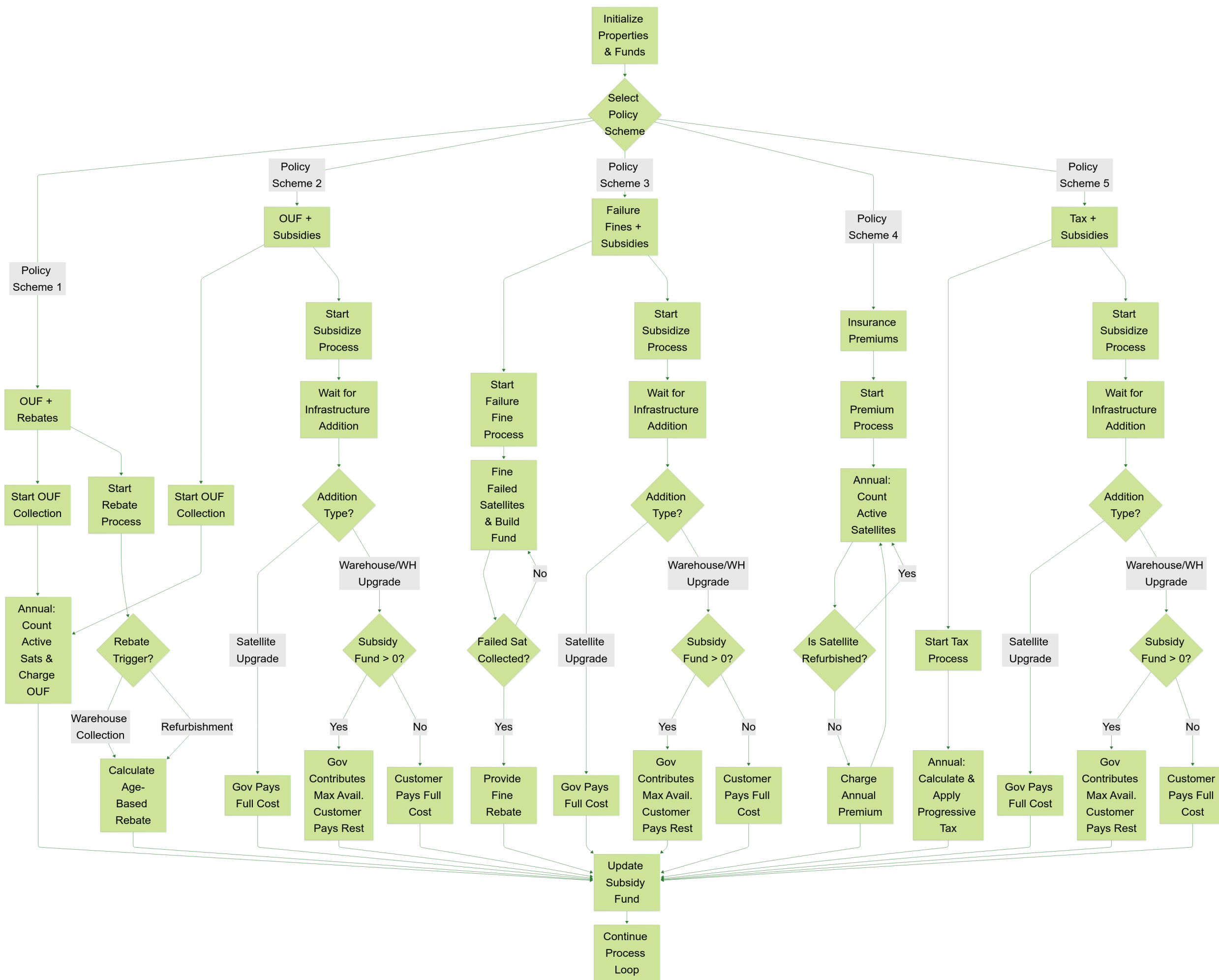


Fig. 4 Policy Scheme Flow Diagram

1. Policy Scheme 1: OUF/Refund

The first option is to introduce an annual OUF for each satellite. The total accrued fee for a particular satellite is credited back to the constellation operator if the satellite is collected and brought to a warehouse. Another option for this scheme is to only credit back the fee if the satellite is refurbished; either on Earth or in space. The refund value is considered within the decision logic for whether the operator should choose to refurbish a particular satellite. It is also included in the decision logic for adding or upgrading warehouses. Since more warehouses means more collection, the refund for each collected satellite could help offset the cost of the infrastructure updates or upgrades.

2. Policy Scheme 2: OUF/Subsidy

The second option is to collect an annual orbital use fee for each satellite and subsidize warehouse purchases and upgrades with the proceeds. This impacts the decision rules for adding or upgrading warehouses by reducing their associated costs by the amount available in the fund generated from the OUFs. This is similar to the Roy et. al. approach to using OUFs to finance the case for on-orbit recycling [19].

3. Policy Scheme 3: Contingent Fines/Subsidy

In this "polluter pays" case, the policy fines all failed satellites, forming a fund to subsidize servicing infrastructure, similar to Policy Scheme 2. If a failed satellite is collected and returned to a warehouse, however, it receives a refund on its fine.

4. Policy Scheme 4: Mandatory Insurance

In this fourth set of policies, the constellation operator is required to pay for the on-orbit insurance for each satellite, based on a percentage of the satellite value. Some researchers, such as Reeseman from the Aerospace Corporation, suggest that OOS and orbital insurance could have a a “unique, symbiotic” relationship since the presence of OOS would reduce the number and severity of claims [26]. Insurance companies would be incentivized to promote OOS and standardization. To capture this relationship, this policy scheme dictates that if the satellite receives service, it no longer requires an annual premium

5. Policy Scheme 5: Subsidy/Taxes

In the final policy scheme, the government taxes a percentage of the constellation operator’s profit at an increasing rate over time. This approach is similar to Policy Scheme 2 and 3 since the proceeds from the taxes go towards subsidizing satellite upgrades, new warehouses, or warehouse upgrades.

V. Results and Analysis

The experiments in this paper compare policy parameters and flexible option settings to evaluate their impact on satellite service outcomes, using the OneWeb constellation as a use case. The first set of experiments contrasts policy-enabled configurations against two baselines: a 1-warehouse baseline with no policy, and a 0-warehouse baseline with no policy. The 1-warehouse baseline has the flexibility to add warehouses while the 0-warehouse baseline does not.

To understand the impact of these policy configurations, their performance is compared to a set of non-policy configurations that vary both the initial number of warehouses and the flexibility of upgrades. These include whether satellites and warehouses begin upgraded, have the option to be upgraded in the future, or cannot be upgraded at all.

This paper employs Value-at-Risk/Gain (VARG) plots to illustrate differences between configurations. These plots display the cumulative distribution of outcomes across each configuration type. This approach highlights not only average values but also tail risks and opportunities.

Results indicate that a single depot paired with flexible options is the most cost-effective configuration for the satellite operator, yielding both economic and emissions benefits. Compared to the 0-warehouse baseline, having one depot significantly reduces emissions. While some policies, such as policy scheme 3 with a $100,000 fine or policy scheme 1 with a $1000 OUF, are comparable in total cost, other policy configurations introduce substantial cost burdens.

To further explore trade-offs, we apply a weighted multi-criteria score that accounts for satellite collections, refurbishments, and de-orbits, while penalizing cost. This enables identification of configurations that maximize operational benefit with minimal economic penalty. Moreover, comparing policy and no-policy configurations via VARG plots reveals that policy interventions substantially reduce the cost per satellite collection and cost per warehouse, reinforcing the value of well-designed incentive schemes.

A. Policy Configuration Comparison

To assess which form of intervention best incentivizes demand for ISAM with the least penalty, a design of experiments (DOE) with parametric policy parameters was run through the described framework. The DOE, tabulated in Table 1 below, contains various parameters for OUFs, refunds, and insurance. By applying the effect of various policy options on the costs and benefits that impact constellation operator decisions, summarized in Table 10, we can identify reward/penalty schemes that provide the best collection and refurbishment rate for the least cost penalty.

Table 1 DOE Configuration Parameters for each Policy Scheme

Parameter	Values	Policy Target
Number of initial warehouses	0 or 1	0 warehouse: No Policy; 1 warehouse: All
Flexible Options	Yes or No	All
Satellite Configuration	(1) satellites start refuelable and repairable or (2) satellites do not start refuelable and repairable	All
Policy Scheme	No Policy, 1, 2, 3, 4, 5	–
Annual OUF	\$1000, \$10000, \$100000	Policy 1
Refund Conditions	(1) refund for collection or (2) refund for refurbishment	Policy 1
Annual OUF	\$2500, \$5000, \$10000, \$20000, \$30000	Policy 2
Contingent Fine	\$100,000, \$1,000,000, \$10,000,000	Policy 3
Annual Premium	0.05%, 0.1%, 0.15%	Policy 4
Annual Tax Percentage	0.002%, 0.005%, 0.01%	Policy 5

Table 2 Comparison for Top Policy Configurations vs. Baselines, by mean total cost

Depot	Configuration Details	Mean Cost	% vs Baseline	Sample Size
1	Policy 3, Fine = \$100,000	\$3.75e+09	**-0.2% (Worse)**	100
1	Policy 1, Rebate = 1, OUF = 1000	\$3.76e+09	**-0.5% (Worse)**	100
1	Policy 1, Rebate = 2, OUF = 1000	\$3.76e+09	**-0.5% (Worse)**	100
1	**No Policy (1-Warehouse Baseline)**	**\$3.74e+09**	**–**	**100**
0	No Policy (0-Warehouse Baseline)	\$3.77e+09	**-0.8% (Worse)**	100

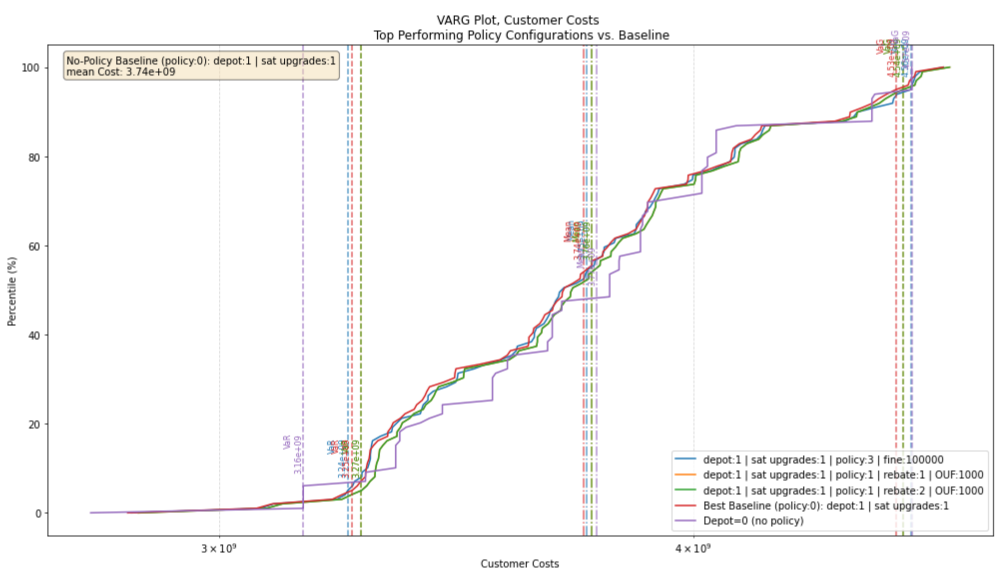


Fig. 5 Total Cost VARG: Top 3 Policy Configurations by Cost vs. Baselines

Comparing the top 3 cost-effective policy configurations by mean cost, presented in Table 2 and Fig. 5, it is evident that the policy configurations have nearly the same total cost over the 30-year scenario span as the 1-warehouse baseline. The top three policy configurations in terms of cost are policy 3 with a fine of $100,000, followed by two configurations of policy scheme 1 where the total of the satellite's yearly $1,000 orbital use fee is refunded back after satellite collection (rebate=1) or refurbishment (rebate=2), respectively. Every configuration slightly improves upon the 0-warehouse baseline, which has a 0.8% higher mean cost than the 1-warehouse baseline. At the 5th percentile case, the 0-depot warehouse presents an opportunity for lower costs compared to the other configurations, but this is only appealing for risk-tolerant satellite constellation operators.

The 1-warehouse baseline offers a significant improvement in emissions compared to the 0-warehouse baseline with a 70% decrease in average NOx emissions. All other policy configurations offer only marginal differences, since reducing launch occurence makes a larger impact on emissions than reducing de-orbit rate, indicating that having any number of warehouses is better than none in terms of emissions. The emissions model is described in the Appendix, in section VII.A.

While these top 3 policy configurations match the 1-warehouse baseline in cost, they don't offer significant improvements to satellite collection or refurbishment rate because they do not significantly influence constellation decision-making. The following Fig. 6 and Table 3 show the top 3 policy configurations in terms of total cost per satellite collection. Figure 6 plots each configuration in terms of total cost.

Table 3 Mean Cost Comparison for (Total Cost)/# Collected Satellites vs. Baselines

Depot	Configuration Details	Mean Cost	% vs Baseline	Sample Size
1	Policy 2, Sat Upgrade: 1, OUF = 30000	$4.47e+09	**-19.6% (Worse)**	100
1	Policy 2, Sat Upgrade: 1, OUF = 20000	$4.21e+09	**-12.4% (Worse)**	100
1	Policy 2, Sat Upgrade: 2, OUF = 30000	$4.47e+09	**-19.4% (Worse)**	100
1	**No Policy (1-Warehouse Baseline)**	**$3.74e+09**	–	**100**
0	No Policy (0-Warehouse Baseline)	$3.77e+09	**-0.8% (Worse)**	100

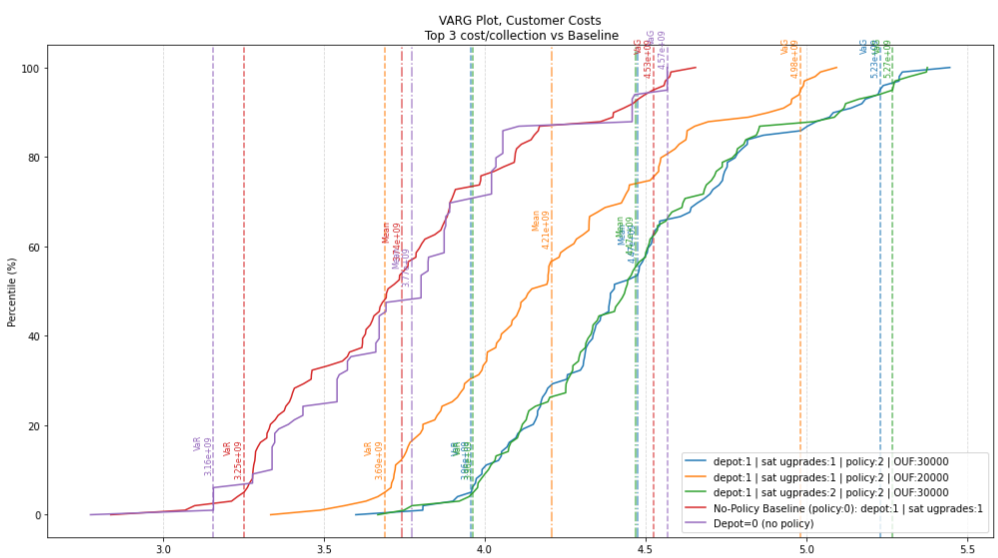


Fig. 6 Total Cost VARG: Top 3 Policy Configurations by (Total Cost)/# Collected Satellites vs. Baselines

All three of the top policy configurations, in terms of cost per satellite collection, use policy scheme 2 (OUF/Subsidy) with either a $20,000 or $30,000 annual OUF. Compared to the 1-warehouse baseline, the mean cost of the cheapest cost/collection configuration, with a $20,000 OUF and flexible satellite upgrades (indicated by satellite upgrades = 1), is 12% greater. Note that satellite upgrades=2 indicates that the satellites start out as refuelable and repairable. These top-3 policy configurations offer greater improvements in collection rate and refurbishment rate, but they are significantly more expensive than the 1-warehouse baseline. Therefore, it is worthwhile to consider a weighted function that identifies the top three configurations in terms of cost, government costs, collection and refurbishment rate, as well as de-orbit reduction.

1. Weighted Function

To identify policy configurations that provide sustainable benefits without a steep cost penalty for the satellite operator, this section uses the following normalized metric equation, with each metric generalized as X, with some metrics inverted to associate higher value with higher performance:

$$\text{metric\_}i = \frac{X_i - X\text{min}}{X_{\text{max}} - X_{\text{min}} + \varepsilon} \tag{1}$$

$$\text{score}_i = w_c \cdot \text{cost}_i + w_k \cdot \text{coll}_i + w_r \cdot \text{ref}_i + w_d \cdot \text{deorb}_i + w_s \cdot \text{subfund}_i \tag{2}$$

$$\text{scoregroup} = \frac{1}{N} \sum_{i=1}^{N} \text{score}_i \tag{3}$$

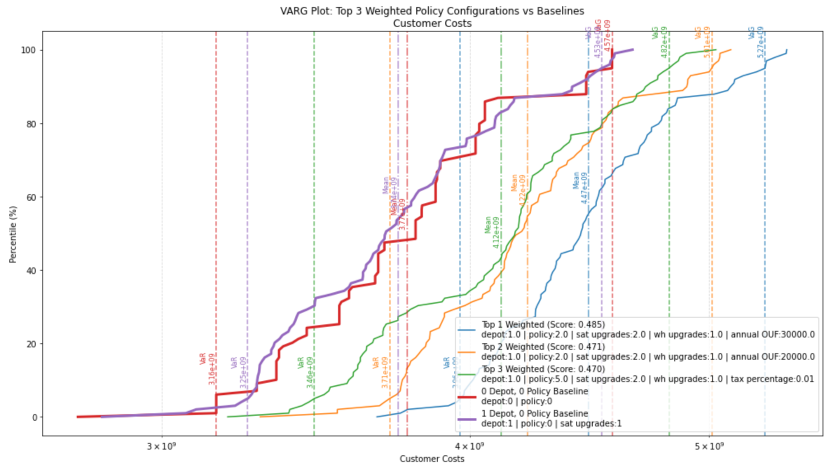
Where weights $w_c = 0.3$, $w_k = 0.2$, $w_r = 0.25$, $w_d = 0.1$, and $w_s = 0.15$, chosen as an example priority set, correspond to cost, collection, refurbishment, deorbiting, and subsidy funding, respectively.

As shown in Fig. 7a and Table 4, the policy configuration of the top 3 weighted configurations with the closest mean costs to the 1-warehouse baseline is policy scheme 5 (tax/subsidy), with an annual tax of 0.01% of constellation profits and satellites that start out as refuelable and repairable. This configuration, with an average total cost of 4.12 Billion Dollars and an average number of 5 warehouses in 30 years, is about 10.0% more expensive than the 1-warehouse baseline, which is an improvement over the top 3 configurations with the best cost per collection. For comparison, note that the 1-warehouse baseline ends the 30-year timeline with an average of 1.66 warehouses. The subsidy fund is included in the weighted function to ensure the government subsidy fund remains in the positive. The average value of the subsidy fund for this configuration is 41.5 Million dollars after the 30 year scenario, which could be credited back to the satellite constellation operator in the future.

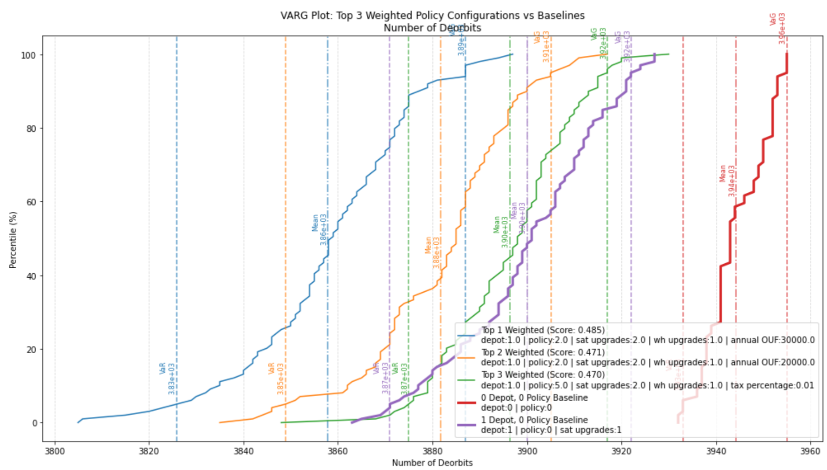
Table 4 Performance Comparison: Best Weighted Policy vs 1-Warehouse Baseline

Configuration Details	Performance Metrics			
	Customer Cost \$ (*10^9)	**Collected Satellites**	**Deorbits**	**Refurbished Satellites**
Weights: Cost=0.3, Collection=0.2, Refurbishment=0.25, Deorbits=0.1, Subfund=0.15				
Best Weighted Policy				
depot:1.0 | policy:5.0 | satellite upgrade:2.0	4.12	32.2	3896.3	23.4
warehouse upgrade:1.0 | tax percentage:0.01				
Weighted Score: 0.470				
1-Warehouse Baseline				
depot:1 | policy:0 | satellite upgrade:1	3.74	30.2	3900.1	11.9
Absolute Difference	+0.38	+2.0	-3.8	+11.5
Percentage Change	+10.0%	+6.6%	-0.1%	+96.2%

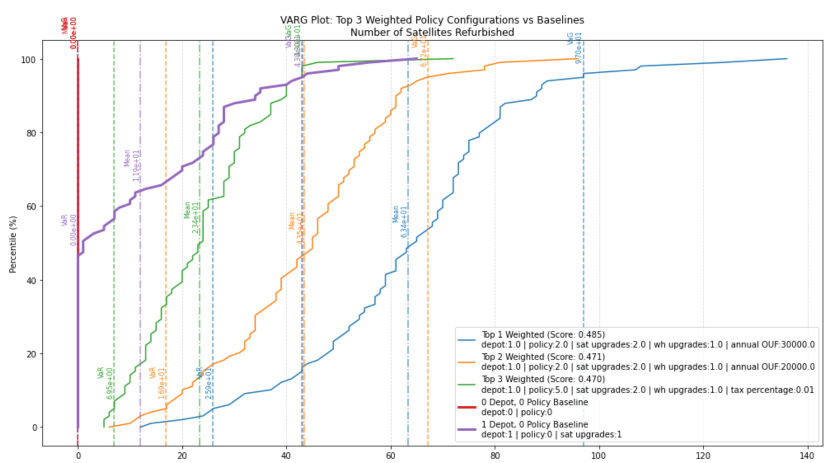
While this configuration does not offer the same degree of de-orbit reduction or collection as the configurations with higher orbital use fees, displayed in Fig. 7b, it does offer nearly twice the number of refurbished satellites compared to the 1-warehouse baseline, as shown in Fig. 7c.



(a) Total Cost VARG: Top 3 Weighted Policy Configurations vs. Baselines



(b) Number of Deorbits VARG: Top 3 Weighted Policy Configurations vs. Baselines



(c) Satellite Refurbishment VARG: Top 3 Weighted Policy Configurations vs. Baselines

Fig. 7 VARG Policy Configuration Analysis

Collecting 32 satellites over the course of 30 years is a relatively low number, only accounting for about 0.8% of de-orbited satellites. However, it provides a starting point for transitioning to a more circular systems in Low Earth Orbit. Enhancing constellation serviceability, such as selecting lower inclinations to accelerate RAAN drift, could improve system efficiency. Satellites equipped for RPOD could autonomously transfer to warehouses, reducing operational costs. While this paper does not explore extending satellite lifespans, doing so could further lower emissions and long-term expenses. Additional revenue opportunities include launch ride-sharing and hosting external payloads. Orbital carriers also attract interest from the U.S. Space Force for their potential to increase responsiveness to on-orbit threats [27].

Ultimately, these result demonstrates the capability of this framework to identify policy schemes that improve long-term sustainability in a manner that complements the goals and strategies of the satellite operator. In this case, it is beneficial for the satellites to start out as both refuelable and repairable, with a low annual tax to subsidize both warehouse infrastructure and the cost delta of the satellite's upgrades.

B. Policy vs. Laissez Faire Comparison

Having compared various policy configurations to the 0-warehouse and 1-warehouse baselines, this section now compares the top performing policy configurations with no-policy configurations other than the 1 and 0-warehouse baselines. The no-policy configurations vary the number of initial warehouses as well as warehouse and satellite options. Each of these configurations are able to add warehouses incrementally, following the same decision rules. This DOE runs 50 scenarios for each set of configuration combination. The variable configuration parameters are shown in Table 5.

Table 5 DOE Parameters for each No-Policy Configuration

Parameter	Values
Number of initial warehouses	0,1,2,3
Flexible Satellite Upgrades	Starts refuelable and repairable (2), upgrade option (1), never upgradable (0)
Flexible Warehouse Upgrades	Starts able to refuel and repair sats (2), upgrade option (1), never upgradable (0)

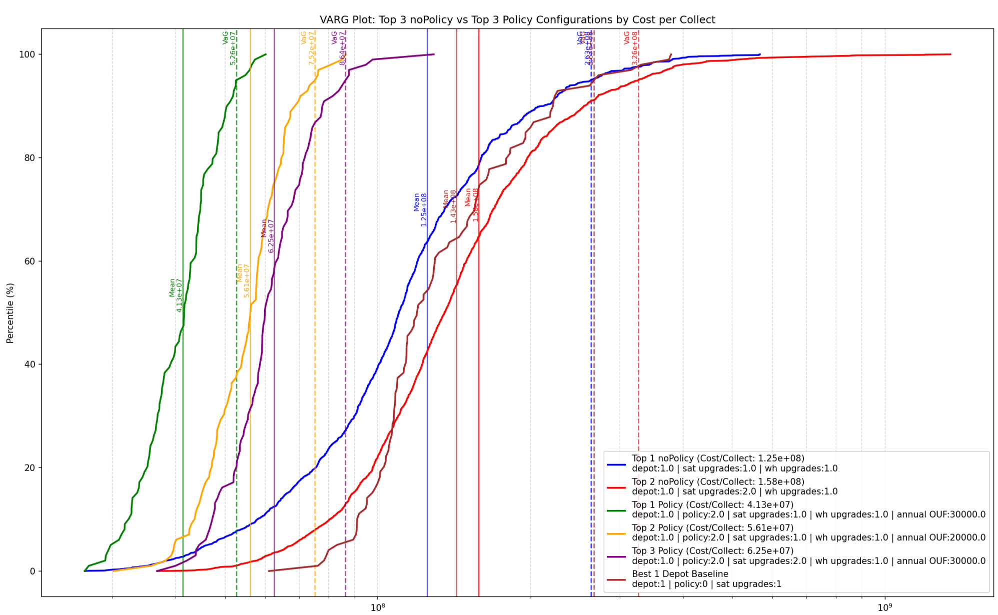


Fig. 8 Cost Per Collected Satellite VARG: Top 3 Policy vs. No-Policy Configurations vs. Baselines, by cost/collection

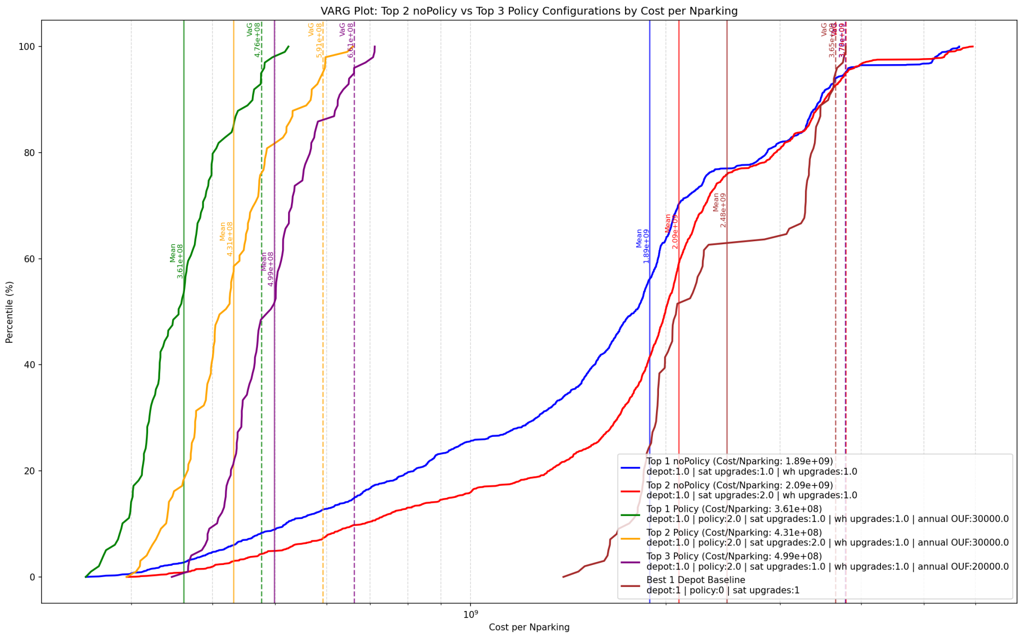


Fig. 9 Cost Per Warehouse VARG: Top 3 Policy vs. No-Policy Configurations vs. Baselines, by cost/Nparking

The top-performing configurations in this no-policy DOE start with 1 warehouse with flexible options for satellite upgrades. This is why all policy configurations begin from this 1-warehouse starting point. Overall, the policy configurations are more cost-effective than the non-policy configurations in terms of cost per collection (Fig. 8) and cost per warehouse (Fig. 9). Figures 8 and 9 show that the top three policy configurations based on cost per collection and cost per warehouse are nearly 4 and 2 times better than the top non-policy configuration, respectively. Table 6 contains the performance breakdown of the top configurations.

Table 6 Mean Cost per Warehouse and per Satellite Collection for Top Configurations

Label	Policy Type	# Warehouses	Satellite Upgrades	Warehouse Upgrades	OUF	Mean Cost	% Above Min
Cost per Warehouse							
Top 1 Policy	2	1	1	1	30000	3.61e+08	0.0%
Top 2 Policy	2	1	2	1	30000	4.31e+08	+19.4%
Top 3 Policy	2	1	1	1	20000	4.99e+08	+38.1%
Top 1 No-Policy	0	1	1	1	–	1.89e+09	+423.3%
Top 2 No-Policy	0	1	2	1	–	2.09e+09	+479.8%
Best 1 Depot	0	1	1	1	–	2.48e+09	+587.6%
Cost per Collect							
Top 1 Policy	2	1	1	1	30000	4.13e+07	0.0%
Top 2 Policy	2	1	1	1	20000	5.61e+07	+36.0%
Top 3 Policy	2	1	2	1	30000	6.25e+07	+51.6%
Top 1 No-Policy	0	1	1	1	–	1.25e+08	+203.4%
Best 1 Depot	0	1	1	1	–	1.43e+08	+246.6%
Top 2 No-Policy	0	1	2	1	–	1.58e+08	+283.3%

Although flexibility in decision-making has its merits for some elements of the infrastructure, this experimental set suggests that starting with upgraded satellites rather than making the decision in the future goes a long way toward improving the cost efficiency of collection and refurbishment within the 30-year period.

VI. Conclusion

While private companies often operate on short future horizons and quarterly goals, governments have both the opportunity and the responsibility to think decades ahead. The CONOPS and flexible strategies introduced in this paper are inherently long-term: leveraging J2 drift to improve maneuverability in LEO is efficient, but slow-going. If policymakers are serious about promoting circular systems in space, they must apply their long-range vision to support sustainable commercial growth without undermining economic viability. The framework proposed here offers a philosophy for evaluating policy options that balance what each sector does best: the private sector's pursuit of efficiency and cost-reduction, and the public sector's ability to apply the right strategic vector to enable sustainable change.

This paper builds on the concepts of Collection-as-a-Service (CAAS) and multi-echelon sparing, applying a framework to assess how different combinations of rewards and penalties shape the business case for ISAM under uncertainty. Using Monte Carlo analysis and decision-rule-driven discrete-event simulations, it identifies the configurations for which ISAM becomes both financially viable and operationally attractive for satellite operators. These insights can guide targeted policy interventions through de-risking, incentivizing sustainable behavior, or enabling critical infrastructure to accelerate adoption.

While the configuration and policy schemes presented in this paper offer an initial example of how the methodology of CAAS paired with flexibility and policy could improve the case for OOS in LEO, there are a number of opportunities for further investigation. For instance, designing a satellite constellation to be more serviceable, such as using a lower constellation inclination for faster RAAN drift rates, could improve the proposed system. Collaborative maneuvering, where satellites, upgraded for RPOD, are able to deliver themselves to a warehouse, could significantly cut costs. This paper does not consider the option to lengthen satellite design life, but this is another possibility for improving both emissions and long-term costs. Opportunities such as launch ride sharing or collaborating with other companies to host commercial and scientific payloads offer additional possibilities for revenue. Orbital carriers are also of interest to the US Space Force, since they offer platforms that could improve tactical responsiveness to threats in orbit. While not included in this paper, these opportunities are worthy of consideration in future work.

The experiments conducted in this study offer quantitative support for the framework proposed. Simulations show that initiating with one warehouse and layering in select policies and flexible options yields a favorable balance between cost and more sustainable operations. Among policy scenarios, a few, particularly those that tightly align incentives with desired servicing outcomes, can improve cost performance, but many introduce significant expense. When viewed through the lens of Value-at-Risk/Gain and weighted multi-attribute scoring, configurations that improve the rate of refurbishments and collection with minimal added cost emerge as clear leaders, such as the policy configuration that features a low annual tax on profits that subsidizes sustainable infrastructure. Making the satellites refuelable and repairable from the start helps improve the cost per collection. Furthermore, the results reveal that policy configurations with OUFs of either \$30,000 or \$20,000 have a far better cost per collection and cost per warehouse compared to no-policy configurations that start with 1 to 3 warehouses. These findings reinforce the premise that long-term, coordinated strategies, particularly those that leverage flexibility and policy in tandem, can improve the economic equation for ISAM in LEO.

To drive meaningful change, the growing environmental externalities of space activity must be internalized to some degree. The results of this study suggest that early, well-aligned policy action, designed with operator incentives and market dynamics in mind, can accelerate the emergence of a sustainable and profitable ISAM ecosystem in LEO. By fostering an environment that values flexibility, collaboration, and long-term investment, stakeholders can take a step closer towards a resilient, circular space economy.

VII. Appendix

Table 7 Deterministic Simulation Parameters

Variable Name	Value/Range
number of planes	18
satellites per plane	36
customer altitude	1200km
parking orbit altitude	796km
inclination	86.4 degrees
number of in-plane spares	2 satellites
satellite dry mass	150 kg[28]
satellite fuel mass	12 kg
dry mass ADR	150 kg [29]
fuel mass ADR	150 kg
ISP ADR	230 s
warehouse max capacity	35 satellites
warehouse initial capacity	5 spare satellites
warehouse fuel mass	500 kg
warehouse dry mass	1000 kg
Xenon cost	$5000/kg [30]
Green monopropellant cost	$100/kg [31] [32]
cost to de-orbit	$10,000.00
discount rate	0.03
Launch cost multiplier for single satellite vs. batch launch	6.5 X [28]

A. Emissions Model

This paper focuses on NO_x emissions due to their well-understood impact on the ozone layer and the availability of models that relate emissions to re-entry mass. The proportional relationship for total NO_x emissions used in this framework is:

$$\text{NOx emissions} \propto 0.175 \cdot m_{\text{Returned to Earth}} + m_{\text{burned in the atmosphere}} \tag{4}$$

To estimate the mass of returning launch vehicles, the model uses the Tsiolkovsky rocket equation for stage separation and second-stage performance and uses publicly available information about existing or developing launch vehicles [33], [34], [35],[36],[37]. The second-stage velocity increment is:

$$\Delta V_2 = I_{sp_2} \cdot g_0 \cdot \ln\left(\frac{M_{\text{sep}}}{M2ndstage_{\text{dry}} + M_{\text{payload}}}\right) \tag{5}$$

The separation mass (M_{sep}) is estimated as:

$$M_{\text{sep}} = M_{\text{launch}} \cdot \exp\left(-\frac{V_{\text{sep}}}{I_{sp_1} \cdot g_0}\right) \tag{6}$$

And the dry mass of the second stage ($M2ndstage_{\text{dry}}$), which contributes to re-entry emissions, is:

$$M2ndstage_{\text{dry}} = M_{\text{sep}} \cdot \exp\left(-\frac{\Delta V_2}{I_{sp_2} \cdot g_0}\right) - M_{\text{payload}} \tag{7}$$

Table 8 Sources of Uncertainty and Modeling Parameters

Uncertain Quantity	Model/Method	Initial Value(s)	Uncertainty Parameters	Eq.
Constellation Revenue	Geometric Random Walk / Log-normal PDF	$1.4B/year	α = 0.059, σ = 0.15	8
Launch Cost	Log-normal PDF with volatility cone [38]	present launch cost per kg, 6.5x for single-sat launch	σ = 0.15	8
Launch Delay	Processing + Exponential	$T_{\text{processing}}$ = 3 months, μ_{launch}=2 months	Exponential with μ_{launch}	9
ADR Launch Delay	Learning Curve + Exponential	min_{time}=0.5 years, $initial_{\text{extraTime}}$=1.5 years, λ=0.2303, μ_{launch}=2 months	Exponential with μ_{launch}	10
Satellite Manufacturing Cost	Log-normal PDF	$900,000 [39]	$alpha\_m$ = -0.075 [40], sigma_m = 0.1 [14, 41, 42].	8
ADR Vehicle Cost	Learning Curve + Time-based decay	$48,000,000 (initial) [42]	$\lambda \sim U(0.1, 0.5)$, $P_{\min} \sim U(0.5, 0.8) * cost_i$, $N_{\max}$ = 1 ADR/plane, r = 0.03	11,12
ADR Collection Success	Learning Curve (Power Law)	$S_0 \sim U(0.7, 0.99)$	$\lambda \sim U(0.05, 0.25)$	13
Space-Based Services (ADR Operation, Refuel, Repair, Obsolete Repair)	Log-normal PDF	$250,000 / $250,000 / $562,500 / $687,500 (repair is 1.25X Earth-based cost)	$\alpha = -0.0375$, $\sigma = 0.1$ (services $\propto$ same path)	8
Warehouse Cost	Learning Curve + Time-based decay	$100,000,000 (initial)	$\lambda \sim U(0.1, 0.5)$, $P_{\min} \sim U(0.5, 0.8) * cost_i$, $N_{\max}$ = 54, r = 0.03	14,15
Earth-Based Services (Repair, Refurbish, Obsolete Repair)	Log-normal PDF	$450,000 / $200,000 / $550,000 (repairable); $855,000 (non-repairable)	$\alpha = -0.075$, $\sigma = 0.1$ (services $\propto$ same path)	8
Warehouse Upgrades (Refuel, Repair Capability)	Log-normal PDF	$8M / $15M	$\alpha = -0.0375$, $\sigma = 0.1$ (capabilities $\propto$ to space-based services path)	8
Satellite Upgrade R&D (Refuelable, Repairable)	Log-normal PDF	$5M / $9M R&D + 6% / 10% cost increase	$\alpha = -0.0375$, $\sigma = 0.1$ on R&D (capabilities $\propto$ to space-based services path)	8
Technology Obsolescence	Weibull Utility Function	N/A	$k = 2$, $\lambda = 1$, $\beta = 2$	16
Failure Time	Exponential (from MTBF)	MTBF from 1 failure/year	Derived from fleet size; Exponential distribution	17,18
Failure Type	Bernoulli Trial	50% inoperable	None (uniform draw)	—
Collision Event Cost	Exponential + Uniform + Cascade Probability	$10,000 base	$\beta = 0.01$, $P_{\text{cascade}} = \min(0.02T, 0.5)$	19,20,21,22

B. Uncertainty Equations

1. Log-normal probability density function for the geometric random walk method

The geometric random walk method is commonly used to model revenue and was used in previous OOS flexibility frameworks [10–12].

$$p_\tau^{(m)}(x) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_m \sqrt{\tau}} \frac{1}{x} \exp\left\{ -\frac{\left(\ln(x) - \left(\alpha_m - \sigma_m^2/2\right)\tau\right)^2}{2\sigma_m^2 \tau} \right\} \tag{8}$$

In the equation above, α_m is the expected revenue rate of return, ω_m is volatility, τ is time, and r is the risk-free interest rate. This method is applied to various sources of uncertainty.

2. Launch Cost and Delay

Launch cost scenarios use log-normal models with volatility cones based on Citi Research projections [38] with a sigma m approximated at 0.15.

Uncertainty is also applied to launch time, with Tprocessing = 3 months and mu_launch = 2 months such that

$$launchTime = Tprocessing + np.random.exponential(launcher.mu\_launch). \tag{9}$$

For ADR mission launched directly from Earth, Tprocessing follows a learning curve as more ADR vehicles are manufactured and launched.

$$adrTprocessing = min_{time} + (initial_{\text{extraTime}} * np.exp(-\lambda * t)) \tag{10}$$

Where min_{time}=0.5, $initial_{\text{extraTime}}$ = 1.5, and λ = 0.2303

3. ADR Vehicle Cost

The cost of an ADR vehicle is modeled using a time-based exponential decay with an initial cost $48,000,000. However, there is also a multiplier applied to the cost based on the learning curve effect:

$$n = \{1, 2, \ldots, N_{\max}\}; \text{value}(n) = P_{\min} + (1 - P_{\min}) \cdot e^{-\lambda n} \tag{11}$$

Where n is the number of ADR vehicles added (starting from 1), $N_{\max}$ is the maximum number of ADR vehicles considered, $P_{\min}$ is the minimum performance level (asymptotic limit), and λ is the learning exponent (controls rate of decay) that is a random value between 0.1 and 0.5.

The time-based reduction, with r = 0.03 (annual reduction rate) and t=years, is given such that:

$$\text{cost\_reduction} = (1 - r)^t \tag{12}$$

4. Space-Based Operations and Costs

ADR vehicles are given a chance of successfully collecting a satellite based on a learning curve trend which is given as follows:

$$n = \{1, 2, \ldots, N_{\max}\}; \text{value}(n) = 1 - (1 - S_0) \cdot n^{-\lambda} \tag{13}$$

In this equation, n is the number of satellites collected (starting from 1), $N_{\max}$ is the maximum number of collected satellites considered (assumed to be 50), after which point the collection probability remains the same, S_0 is the starting point (initial value at $n = 1$), which is a random value that ranges between 0.7 and 0.99, and λ is the learning exponent (controls the rate of improvement), which is a random value that ranges between 0.05 and 0.25

The cost of each ADR operation is assumed to start at $250,000 and this value changes over time following the same geometric random path as the other space-based operations. These space-based services are proportional to the same random path because it is assumed that they are all related to the same general capabilities.

5. Warehouse/Depot Cost

The warehouse cost uncertainty is modeled in the same way as the ADR vehicle cost, with initial cost of 100 million dollars that decreases with each new warehouse added to the system. The equation for this learning-curve-based reduction is given as:

$$n = \{1, 2, \dots, N_{\max}\}; \text{value}(n) = P_{\min} + (1 - P_{\min}) \cdot e^{-\lambda n} \tag{14}$$

In the equation above, n is the number of warehouses added (starting from 1), $N_{\max}$ is the maximum number of warehouses considered, $P_{\min}$ is the minimum performance level (asymptotic limit), λ is the learning exponent (controls rate of decay) and is a random value between 0.1 and 0.5. Just like the ADR vehicle cost, there is also a time-based reduction where r = 0.03 (annual reduction rate) and t is time in years.

$$\text{cost\_reduction} = (1 - r)^t \tag{15}$$

6. Technology Obsolescence

This framework uses a Weibull-based utility function to reduce satellite revenue after it has reached the time of obsolescence, based the utility function $u(t)$, defined by on Geng et. al. [43]. The Geng model uses 3-parameter Weibull distribution with $\beta = 2$. The intensity metric is determined randomly for each scenario and time to obsolescence for each scenario comes from a Weibull distribution with shape, k = 2 and scale, lambda = 1.

$$\begin{aligned} u_i(t) &= u_{o,i} e^{-\left(\frac{(t - T_{obs,i})^{\beta}}{\theta_{obs,i}}\right)} \quad \text{for } t \geq T_{obs,i}, \\ u_{\text{total}} &= \sum_i u_i(t). \end{aligned} \tag{16}$$

7. Failure Rates

OneWeb has experienced 4 satellite failures in 4 years [44] [45]. This paper therefore sets failure rate to 1 satellite fail per year, which is converted to mean time between failure (MTBF) using the following equation:

$$MTBF = ((1/(failureRate/(numPlanes * totalSatellitesPerPlane))) \tag{17}$$

Every satellite is assigned a time to failure based on the MTBF:

$$time2failure = np.random.exponential(scale = self.MTBF) \tag{18}$$

8. Cost of Collision Avoidance and Collision Events

$$P_{\text{collision}} = 1 - e^{-\beta \cdot N_{\text{fail}} \cdot T} \tag{19}$$

In this equation, N_{fail} is the number of failed satellites, T is the number of years, and $\beta = 0.01$, the collision hazard rate per satellite per year. The base cost of a collision-related event is defined as C_{base} = 10,000. The probability of a cascade-type catastrophic event is:

$$P_{\text{cascade}} = \min(0.02 \cdot T_{\text{cascade}}, 0.5) \tag{20}$$

The collision cost is then drawn from a uniform distribution, based on whether a cascade occurs:

$$C_{\text{collision}} = \begin{cases} C_{\text{base}} \cdot U(1000, 10000), & \text{with probability } P_{\text{cascade}} \\ C_{\text{base}} \cdot U(1, 1000), & \text{with probability } 1 - P_{\text{cascade}} \end{cases} \tag{21}$$

The actual cost incurred is:

$$C = \begin{cases} C_{\text{collision}}, & \text{if a collision occurs (with probability } P_{\text{collision}}) \\ 0, & \text{otherwise} \end{cases} \tag{22}$$

Table 10 Summary of Simulation Costs

Cost Type	Details
Initial cost	Includes the cost of existing satellites, warehouses, and ADR vehicles at the start of the simulation, including any applicable upgrades.
Cost to directly replace failed satellites	Triggered when no in-plane spare or nearby warehouse is available. Includes cost of the satellite, its fuel, and a single-satellite launch.
Cost to launch ADR mission directly from Earth	Applied when no ADR vehicle is available nearby. Includes ADR hardware, launch cost, and operation cost.
Cost to replace planes of satellites	Scheduled batch replacement of aging planes. Includes costs of satellites, fuel, and launch for all replacements.
Cost to resupply warehouses	Includes spare satellites, satellite and warehouse fuel, new ADRs (if ordered), upgrades, and return cost for old satellites if sent to Earth.
Cost to service satellites on Earth	Incurred when satellites return and are refurbished or repaired based on NPV evaluation. Includes servicing and recommissioning costs.
Cost of lost revenue due to obsolescence or lost coverage	Revenue loss due to satellites being down or obsolete. Obsolescence reduces utility; gaps in coverage incur cost based on revenue loss per day.
Cost associated with collision avoidance or events	Incurred when collision avoidance maneuvers or actual collisions occur, as defined by the uncertainty model.
Cost of ADR operations in space	Cost to operate ADR missions within space (e.g., satellite retrieval and towing to warehouse).
Cost to upgrade satellites	Applied when customers invest in satellite upgrades, such as refuelability or repairability.
Cost to upgrade warehouses	Applied when a warehouse is upgraded (e.g., to include fuel or repair capabilities).
Cost to service satellites in space	Incurred when satellites are repaired or refueled on-orbit using warehouse capabilities.
Cost to de-orbit satellites	Applied when a satellite is actively de-orbited instead of refurbished or reused.
Cost of adding new warehouses	Applied when customers expand capacity by deploying new orbital warehouse facilities.

Table 9 Cost Assumptions

Variable Name	Value	Justification
Satellite Unit Cost	$900,000	Based on estimated OneWeb satellite cost [39]
Earth Refurbishment (General)	$200,000	Includes labor, testing, parts and upgrades, and facilities. It's assumed that refurbishing is roughly 20-40% of manufacturing a new satellite, based on the economics of refurbishing reusable rockets, which is 65% cheaper than launching new [46]
In-space/Earth Repair (Repairable Satellite Failure)	$450,000	More effort than refurbishment, roughly half the cost of a new satellite
In-space/Earth Repair (Obsolescence, Repairable)	$550,000	More expensive than repair due to payload upgrade and related testing
Earth Repair (Obsolescence, Non-repairable)	$855,000	Requires more extensive labor to swap a payload in a satellite not meant to be repaired, roughly the same cost as a new satellite
Satellite Refuel Upgrade, R&D	$5,000,000	Redesign for mechanical and fluid interface, propulsion system adjustments, electrical & software integration, testing and certification
Satellite Refuel Upgrade, satellite cost multipler	x1.06	Refueling hardware, specialized valves, necessary ops, addt'l testing
Satellite Repair Upgrade, R&D	$9,000,000	Design modularization, standardized interfaces, on-board failure monitoring, testing, qualification
Satellite Repair Upgrade, satellite cost multipler	x1.1	Modular wire harnessing, specialized panels and fasteners, board/box designs with fewer soldered components, addt'l sensors
Warehouse Refuel Upgrade	$8,000,000	Xenon storage and pressure management, refueling system with specialized docking, precision control systems, diagnostic monitoring, coordination between depot and satellite, training, certification, and testing
Warehouse Repair Upgrade	$15,000,000	Diagnostic systems and related sensors, robotic capability and tooling, spare parts, power systems for satellite battery test & recharge, specialized software, training, and testing
ADR Vehicle Cost	$48,000,000	Based on $16 million (USD) Astroscale contract that covers about 1/3 of vehicle cost [42]
ADR Operation	$250,000	Includes the cost for ground support, GNC, RPOD, system checks, mission operations
In-Space Refueling Operation	$250,000	Includes the cost for ground support, controls, robotic operation, system checks, depreciation of hardware, labor, mission operations
Warehouse Cost	$100,000,000	Based on analogous servicing spacecraft budgets, such as DARPA RSGS [47] and MEV-2 [48], which have more capability than initial spare warehouse configuration. Can also be compared to the scale of large GEO satellites, such as Intelsat 10-02 [48], factoring out launch cost to GEO
2nd stage return delivery cost	20% of launch cost ($/kg)	Stoke's reusable 2nd stage capacity is about 40% of non-reusable 2nd stage capacity [49], so the return cost accounts for half the payload opportunity cost
Deorbit Cost	$10,000	Based on propellant and operations

References

[1] Boley, A. C., and Byers, M., "Satellite mega-constellations create risks in Low Earth Orbit, the atmosphere and on Earth," *Scientific Reports*, Vol. 11, No. 1, 2021, p. 10642. https://doi.org/10.1038/s41598-021-89909-7, URL https://doi.org/10.1038/s41598-021-89909-7.

[2] Ryan, R. G., Marais, E. A., Balhatchet, C. J., and Eastham, S. D., "Impact of Rocket Launch and Space Debris Air Pollutant Emissions on Stratospheric Ozone and Global Climate," *Earth's Future*, Vol. 10, No. 6, 2022, p. e2021EF002612. https://doi.org/https://doi.org/10.1029/2021EF002612, URL https://doi.org/10.1029/2021EF002612.

[3] Jones, K. L., and Jain, A. K., "The Green Circularity: Life Cycle Assessments in the Space Industry," Tech. rep., Aerospace Corporation, Segundo, 3 2023. URL https://csps.aerospace.org/sites/default/files/2023-04/Jones-Jain_GreenCircularity_20230331.pdf.

[4] Brown, M. K., Lewis, H. G., Kavanagh, A. J., and Cnossen, I., "Future Decreases in Thermospheric Neutral Density in Low Earth Orbit due to Carbon Dioxide Emissions," *Journal of Geophysical Research: Atmospheres*, Vol. 126, No. 8, 2021, p. e2021JD034589. https://doi.org/https://doi.org/10.1029/2021JD034589, URL https://doi.org/10.1029/2021JD034589.

[5] Ikeya, K., and Ho, K., *Analysis of Cooperative and Non-Cooperative Architectures for Multi-Plane On-Orbit Refueling*, 2023. https://doi.org/10.48550/arXiv.2302.14563.

[6] Zhao, Z., Zhang, J., Li, H.-y., and Zhou, J.-y., "LEO cooperative multi-spacecraft refueling mission optimization considering J2 perturbation and target's surplus propellant constraint," *Advances in Space Research*, Vol. 59, No. 1, 2017, pp. 252–262. https://doi.org/https://doi.org/10.1016/j.asr.2016.10.005, URL https://www.sciencedirect.com/science/article/pii/S0273117716305658.

[7] Luu, M. A., and Hastings, D. E., "On-Orbit Servicing System Architectures for Proliferated Low-Earth-Orbit Constellations," *Journal of Spacecraft and Rockets*, Vol. 59, No. 6, 2022, pp. 1946–1965. https://doi.org/10.2514/1.A35393, URL https://doi.org/10.2514/1.A35393.

[8] Luu, M., and Hastings, D. E., "Valuation of On-Orbit Servicing in Proliferated Low-Earth Orbit Constellations," *ASCEND 2020*, American Institute of Aeronautics and Astronautics, 2020. https://doi.org/doi:10.2514/6.2020-4127, URL https://doi.org/10.2514/6.2020-4127.

[9] Legge, R. S., "Optimization and Valuation of Reconfigurable Satellite Constellations Under Uncertainty," Ph.D. thesis, Massachusetts Inst. of Technology, 2014.

[10] Lamassoure, E. S., "A Framework to Account for Flexibility in Modeling the Value of On-Orbit Servicing for Space Systems," Ph.D. thesis, MIT, 6 2001. URL file:///C:/Users/madel/OneDrive/Documents/thesis/49876700-MIT.pdf.

[11] Saleh, J. H., Lamassoure, E., and Hastings, D. E., "Space Systems Flexibility Provided by On-Orbit Servicing: Part 1," *Journal of Spacecraft and Rockets*, Vol. 39, No. 4, 2002, pp. 551–560. https://doi.org/10.2514/2.3844, URL https://doi.org/10.2514/2.3844.

[12] Lamassoure, E., Saleh, J. H., and Hastings, D. E., "Space Systems Flexibility Provided by On-Orbit Servicing: Part 2," *Journal of Spacecraft and Rockets*, Vol. 39, No. 4, 2002, pp. 561–570. https://doi.org/10.2514/2.3845, URL https://doi.org/10.2514/2.3845.

[13] Bowne, M., Sarton du Jonchay, T., and Mavris, D., "Collection-As-A-Service to Incentivize On-Orbit Servicing in LEO," 2025.

[14] Jakob, P. C. M., Ho, K., Shimizu, S., and Yoshikawa, S., "Optimal satellite constellation spare strategy using multi-echelon inventory control with stochastic demand and lead times," *ArXiv*, Vol. abs/1807.02685, 2018. URL https://api.semanticscholar.org/CorpusID:49651304.

[15] United States Government Accountability Office, "Large Constellations of Satellites: Mitigating Environmental and Other Effects," 2022. URL https://www.gao.gov/assets/gao-22-105166.pdf.

[16] Shah, P. A., Chen, Z. J., and Rowings, S. A., "SPACE EXPLORATION HOLDINGS, LLC'S FINAL RESPONSE BRIEF AS INTERVENOR FOR RESPONDENT ," , 12 2021. URL https://cdn.arstechnica.net/wp-content/uploads/2021/10/spacex.pdf.

[17] Adilov, N., Alexander, P., and Cunningham, B., "An Economic Analysis of Earth Orbit Pollution," *Environmental & Resource Economics*, Vol. 60, No. 1, 2015, pp. 81–98. URL https://EconPapers.repec.org/RePEc:kap:enreec:v:60:y:2015:i:1:p:81-98.

[18] Rao, A., Burgess, M. G., and Kaffine, D., "Orbital-use fees could more than quadruple the value of the space industry," *Proceedings of the National Academy of Sciences*, Vol. 117, No. 23, 2020, pp. 12756–12762. https://doi.org/10.1073/pnas.1921260117, URL https://doi.org/10.1073/pnas.1921260117.

[19] Sinha Roy, S., Shi, Q., Guariniello, C., and DeLaurentis, D. A., “Analysis of the Business Case for an On-orbit Space Debris Recycling Facility,” *AIAA SCITECH 2023 Forum*, American Institute of Aeronautics and Astronautics, Reston, Virginia, 2023. https://doi.org/10.2514/6.2023-0071.

[20] Macauley, M. K., “The economics of space debris: Estimating the costs and benefits of debris mitigation,” *Acta Astronautica*, Vol. 115, 2015, pp. 160–164. https://doi.org/https://doi.org/10.1016/j.actaastro.2015.05.006, URL https://www.sciencedirect.com/science/article/pii/S0094576515001873.

[21] Lucas-Rhimbassen, M., Santos, C., Long, G. A., and Rapp, L., “Conceptual model for a profitable return on investment from space debris as abiotic space resource,” *8 TH EUROPEAN CONFERENCE FOR AERONAUTICS AND SPACE SCIENCES (EUCASS)*, EUCASS, Madrid, 2019. URL https://www.eucass.eu/doi/EUCASS2019-0602.pdf.

[22] Lin, J., “Exploring Flexible Strategies in Engineering Systems Using Screening Models,” Ph.D. thesis, MIT, 12 2008.

[23] Sandler, A. J., and Craig, B., “FCC Advances Its Space and Satellite Agenda,” Tech. rep., Pillsbury, 3 2024.

[24] FCC, “In the Matter of Space Innovation Mitigation of Orbital Debris in the New Space Age,” Tech. rep., 2022.

[25] Rainbow, J., “Astroscale unlocks remaining space agency funds to de-orbit OneWeb satellite,” , 7 2024. URL https://spacenews.com/astroscale-unlocks-remaining-space-agency-funds-to-de-orbit-oneweb-satellite/.

[26] Reesman, R., “ASSURANCE THROUGH INSURANCE AND ON-ORBIT SERVICING,” Tech. rep., Aerospace Corporation, 2 2018. URL https://aerospace.org/sites/default/files/2018-05/OnOrbitServicing.pdf.

[27] Calvelli, F., and Saltzman, C. B., “U.S. Space Force Commercial Space Strategy,” Tech. rep., U.S. Space Force, 4 2024.

[28] Jakob, P., Shimizu, S., Yoshikawa, S., and Ho, K., “Optimal Satellite Constellation Spare Strategy Using Multi-Echelon Inventory Control,” *Journal of Spacecraft and Rockets*, Vol. 56, No. 5, 2019, pp. 1449–1461. https://doi.org/10.2514/1.A34387, URL https://doi.org/10.2514/1.A34387.

[29] Astroscale, “Missions,” , 2023. URL https://astroscale.com/missions/.

[30] SETS, “Xenon, Krypton, or Argon Propellants for Hall Thruster: Efficiency, Properties, Applications, and Cost,” , 2024. URL https://sets.space/xenon-krypton-or-argon-propellants-for-hall-thruster-efficiency-properties-applications-and-cost/.

[31] Iridium, “Hydrazine – Toxic for humans, but satellites love it,” , 2017. URL https://www.iridium.com/blog/hydrazine-toxic-for-humans-but-satellites-love-it/#:~:text=Typical%20cost%20is%20around%20$100,plans%20are%20all%20very%20expensive.

[32] Jewett, R., “Astroscale Hopes ADRAS-J Mission Will Lay the Groundwork for Commercial Debris Removal,” , 2023. URL https://www.satellitetoday.com/sustainability/2023/09/28/astroscale-hopes-adras-j-mission-will-lay-the-groundwork-for-commercial-debris-removal/.

[33] Volosin, J. I. M., “Psyche, Falcon Heavy,” , 10 2023. URL https://everydayastronaut.com/psyche-falcon-heavy/#:~:text=The%20Falcon%20Heavy%20second%20stage,an%20ISP%20of%20348%20seconds.

[34] Beck, P., “Electron, Payload User Guide,” , 11 2022. URL https://www.rocketlabusa.com/launch/electron/#:~:text=First%20Stage,Payload%20User’s%20Guide.

[35] Stoke, “Nova: Engineered for full and rapid reuse,” , 2025. URL https://www.stokespace.com/nova/.

[36] Taylor, J., “Press Kit, SpaceX CRS-6 Mission,” Tech. rep., SpaceX, 4 2015.

[37] Beck, P., and Darley, M., “Return To Sender: Lessons Learned From Rocket Lab’s First Recovery Mission,” *Small Satellite Conference*, 2021. URL https://digitalcommons.usu.edu/cgi/viewcontent.cgi?article=5031&context=smallsat.

[38] Citi Global Perspectives & Solutions, “The Dawn of a New Age,” Tech. rep., Citi, 5 2022. URL https://www.citigroup.com/global/insights/citigps/space_20220509.

[39] Henry, C., and Berger, B., “Amid concerns, OneWeb gets vague about constellation’s cost,” , 9 2018. URL https://spacenews.com/amid-concerns-oneweb-gets-vague-about-constellations-cost/.

[40] Adilov, N., Alexander, P., Cunningham, B., and Albertson, N., “An analysis of launch cost reductions for low Earth orbit satellites,” *Economics Bulletin*, Vol. 42, No. 3, 2022.

[41] Leonard, R., and Williams, I. D., "Viability of a circular economy for space debris," *Waste Management*, Vol. 155, 2023, pp. 19–28. https://doi.org/https://doi.org/10.1016/j.wasman.2022.10.024, URL https://www.sciencedirect.com/science/article/pii/S0956053X22005104.

[42] Rainbow, J., "Astroscale gets funds for 2024 debris-removal mission," , 5 2022. URL https://spacenews.com/astroscale-gets-funds-for-2024-debris-removal-mission/.

[43] Geng, F., Dubos, G. F., and Saleh, J. H., "Spacecraft obsolescence: Modeling, value analysis, and implications for design and acquisition," *2016 IEEE Aerospace Conference*, 2016, pp. 1–13. https://doi.org/10.1109/AERO.2016.7500642.

[44] Selding, P., "OneWeb, Eutelsat call for tighter satellite-disposal regulations; 4 of OneWeb's 634 satellites have failed in orbit," , 6 2023. URL https://www.spaceintelreport.com/oneweb-eutelsat-call-for-tighter-satellite-disposal-regulations-4-of-onewebs-634-satellites-have-failed-in-orbit/#:~:text=PARIS%E2%80%94%20OneWeb%20said%20four%20of,to%20remain%20in%20position%20indefinitely.

[45] Rainbow, J., "Eutelsat scales back OneWeb Gen 2 upgrade plan," , 2 2024. URL https://spacenews.com/eutelsat-scales-back-oneweb-gen-2-upgrade-plan/#:~:text=Most%20of%20the%20633%20satellites,extending%20to%20around%202027%2D2028.

[46] Stockley, A., "The Rise of Reusable Rockets: Transforming the Economics of Space Travel," , 4 2023. URL https://www.kdcresource.com/insights-events/the-rise-of-reusable-rockets-transforming-the-economics-of-space-travel/#:~:text=Unsurprisingly%2C%20it%E2%80%99s%20much%20cheaper%20to%20refurbish%20and%20relaunch%20a%20rocket%20than%20it%20is%20to%20build%20a%20new%20one%20%E2%80%93%20it%20can%20be%20up%20to%2065%25%20cheaper%2C%20with%20a%2030x%20lower%20cost%20overrun.%20Reusable%20rockets%20also%20use%20less%20fuel%20than%20their%20expendable%20counterparts%2C%20making%20them%20comparatively%20better%20for%20the%20environment.

[47] Erwin, S., "DARPA's satellite servicing robot to get another shot," , 7 2019. URL https://spacenews.com/darpas-satellite-servicing-robot-to-get-another-shot/.

[48] Gannon, P., "Another MEV Rescue Mission," , 9 2020.

[49] Foust, J., "Stoke Space raises $260 million," , 1 2025. URL https://spacenews.com/stoke-space-raises-260-million/.