

# From Theory to Practice: An Operationally-Focused IP Model for GSaaS Procurement

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**Abstract**— While Integer Programming (IP) provides a powerful theoretical framework for optimizing satellite ground station networks, a significant gap exists between mathematically optimal models and operationally viable ones. Standard IP formulations that solely maximize data throughput often recommend fragmented and impractically complex networks. This paper resolves this theory-practice gap by introducing an enhanced IP model that incorporates an Operational Complexity Penalty (OCP), a regularization term that penalizes network size to favor consolidated, manageable solutions. To ensure the validity of this penalty, we introduce a data-driven normalization method that makes the model self-calibrating. The penalty weight is dynamically scaled based on the median data-to-cost efficiency of the specific network scenario, making the trade-off between performance and complexity economically rational.

Through a series of simulated trade studies on a 5-satellite constellation, we demonstrate the powerful utility of this approach. The results from our Pareto frontier analysis show that the OCP-enhanced model can reduce network complexity by over 54% compared to the unconstrained baseline while retaining nearly 85% of the maximum possible data throughput. This key finding reveals that a substantial portion of the baseline network is comprised of operationally expensive assets offering only marginal utility, confirming that a pure data-maximization objective leads to inefficient resource allocation. Furthermore, our budget sensitivity analysis confirms that under realistic financial constraints, the model consistently produces more capital-efficient networks, delivering superior data return per station activated. The significance of this work lies in its transformation of the abstract ground station selection problem into a practical, strategic planning tool, providing mission operators with a quantitative method to balance performance, complexity, and cost.

## 1. INTRODUCTION

The proliferation of Low Earth Orbit (LEO) satellite constellations has fundamentally altered the space economy, shifting the paradigm of ground segment architecture from bespoke, dedicated antennas to a dynamic, multi-provider marketplace known as Ground-Station-as-a-Service (GSaaS). While this model offers unprecedented flexibility and scalability, it introduces a formidable optimization challenge: how to select an optimal portfolio of providers and locations from a vast and heterogeneous global network to meet mission objectives without incurring exorbitant operational costs.

The seminal work by Eddy et al. [1] established a robust theoretical foundation for solving this problem, rigorously formulating it as an Integer Programming (IP) task. This approach provides a powerful framework for maximizing objectives such as data throughput or minimizing mission cost. However, a critical gap persists between the mathematical abstraction and the exigencies of real-world operations. Direct application of these theoretical models often yields solutions that, while mathematically optimal, are operationally untenable—recommending a fragmented and unwieldy network of dozens of disparate ground stations, creating an immense burden of contractual overhead, logistical management, and multiple points of failure.

This paper confronts and resolves this critical theory-practice gap. We claim that a truly optimal solution must balance mathematical performance with operational viability. To achieve this, we introduce an enhancement to the baseline IP model: the Operational Complexity Penalty (OCP). This regularization term is integrated directly into the objective function, penalizing network fragmentation to favor consolidated and manageable solutions. However, this presents a challenge, as the objective function must compare network complexity (measured in stations) with data throughput (measured in bits). To solve this, our model introduces a data-driven normalization method. It analyzes all potential contacts to determine the median cost of data (in bits per dollar) for that specific scenario. This value is then used to convert the monetary penalty for adding a station,  $P_{base}$ , into an equivalent "data cost." This self-calibrating mechanism allows the optimizer to make a direct and rational trade-off, eliminating the need for arbitrary parameter tuning.

## TABLE OF CONTENTS

1. INTRODUCTION .....	1
2. PROBLEM FORMULATION .....	2
3. EXPERIMENTAL SETUP.....	2
4. RESULTS AND DISCUSSION .....	3
5. CONCLUSION .....	4
APPENDICES.....	5
A. VALIDATION OF DATA THROUGHPUT .....	5
ACKNOWLEDGEMENTS.....	5
REFERENCES .....	5
BIOGRAPHY .....	6

## 2. PROBLEM FORMULATION

This section details the mathematical model. We begin with the baseline IP formulation inspired by Eddy et al. [1] and then introduce our novel enhancements.

### *Integer Programming Model*

The ground station selection problem is formulated as an integer program (IP). Let  $S$  be the set of satellites,  $L$  be the set of potential ground station locations,  $P$  be the set of providers, and  $C$  be the set of all possible communication contacts over a simulation window  $T_{sim}$ .

Our primary decision variable is a binary variable  $c_i \in \{0, 1\}$  for each contact  $i \in C$ , where  $c_i = 1$  if the contact is selected and 0 otherwise. Auxiliary binary variables  $l_j \in \{0, 1\}$  and  $p_k \in \{0, 1\}$  indicate the selection of location  $j \in L$  and provider  $k \in P$ , respectively. The baseline objective is to maximize the total data volume downlinked:

$$\text{maximize} \sum_{i \in C} D_i \cdot c_i$$

where  $D_i$  is the total data (in bits) that can be downlinked during contact  $i$ .

To ensure a valid and physically realizable schedule, the model must adhere to a set of fundamental constraints. Our formulation incorporates the core hierarchical and physical limitations as rigorously defined by Eddy et al. [1]. These include:

- **Linking Constraints:** These enforce the logical hierarchy of the network. The selection of any given contact ( $c_i = 1$ ) mandates the selection of its corresponding location ( $l_j = 1$ ), and the selection of any location mandates the selection of its parent provider ( $p_k = 1$ ).
- **Station Contact Exclusion:** This constraint ensures that a single ground station antenna cannot service two different satellites simultaneously. If two contacts,  $c_i$  and  $c_j$ , at the same location have overlapping time intervals, at most one can be selected.
- **Satellite Contact Exclusion:** This constraint enforces that a single satellite cannot communicate with two different ground stations simultaneously. Similarly, if two contacts involving the same satellite have overlapping time intervals, at most one can be selected.

This baseline formulation provides the necessary structure upon which our operational enhancements are built.

### *Operational Complexity Penalty (OCP)*

A key limitation of the baseline IP model is its susceptibility to including network assets for only marginal gains. The objective to purely maximize data throughput will activate an additional ground station for any non-zero increase in data, regardless of how small. This can lead to solutions that are brittle and over-fitted, where significant network complexity is added for trivial performance improvements.

To address this, we introduce an Operational Complexity Penalty (OCP). This term acts as a regularization mechanism, a standard technique for improving solution robustness. The OCP enforces a minimum utility threshold for station activation, ensuring that a station is only included in the final network if its contribution to the total data downlink is significant enough to outweigh the penalty. This prevents the optimizer from chasing marginal utility and promotes a more

consolidated and robust network architecture.

The OCP is a regularization term that applies a penalty,  $\lambda$ , for each unique ground station location  $l_j$  activated in the solution. This transforms the objective from a simple maximization of data into the maximization of a utility function,  $U$ , which balances raw throughput against network simplicity. The modified objective is therefore formulated as:

$$\text{maximize } U = \left( \sum_{i \in C} D_i \cdot c_i \right) - \left( \sum_{j \in L} \lambda \cdot l_j \right) \quad (1)$$

The first term represents the total data gain, while the second term represents the penalty for complexity. The penalty term,  $\lambda$ , acts as a powerful disincentive, guiding the optimizer to reject solutions that rely on a large number of disparate stations to achieve only marginal data gains. It forces the model to seek network consolidation, mirroring the preference of a rational human operator.

### *Adaptive Objective Function Normalization*

The effectiveness of the OCP depends on a systematic determination of the penalty weight,  $\lambda$ . A manually-tuned or arbitrary weight would be scientifically unsound, as the utility function's two terms—data throughput (measured in bits) and network complexity (a unitless count)—are incomensurable.

To resolve this, our method makes the terms comparable by grounding the penalty in the economics of the specific scenario. This is achieved by defining the final penalty,  $\lambda$ , as the product of a base monetary penalty for station activation,  $P_{base}$ , and a data-cost conversion factor,  $k$ :

$$\lambda = P_{base} \cdot k \quad (2)$$

The conversion factor  $k$  represents the opportunity cost of data, measured in bits per dollar. We derive  $k$  from the data of the problem itself. It is calculated as the median cost-efficiency across all potential contacts in the simulation window:

$$k = \text{median} \left( \frac{D_i}{\text{Cost}_i} \right) \quad \forall i \in C \text{ where } \text{Cost}_i > 0 \quad (3)$$

Here,  $\text{Cost}_i$  is the total operational cost to execute contact  $i$ . By using the median, we establish a robust benchmark of the network's typical efficiency, resistant to outliers from extremely cheap or expensive contacts.

This technique removes the need for arbitrary parameter tuning. It ensures the OCP acts as a rational economic agent, making trade-offs based on a coherent, data-driven valuation of network complexity. The entire model becomes self-calibrating across diverse network and cost scenarios.

## 3. EXPERIMENTAL SETUP

To provide a comprehensive evaluation of the OCP-enhanced model, we designed a validation framework with the primary

objective of quantitatively assessing its performance against the critical benchmark established in prior work: the unconstrained IP optimization model. This framework is designed to test the models' performance and behavior under realistic operational constraints.

### Models Under Evaluation

Two distinct models are compared throughout this analysis:

- The Unconstrained IP Baseline:** This is the theoretical model proposed by Eddy et al. [1], which seeks to maximize data throughput by selecting from all available providers and stations without penalizing network complexity.
- The OCP-Enhanced Model:** This is our proposed model, which maximizes a utility function that balances data throughput with the Operational Complexity Penalty, as defined in Eq. 1.

### Evaluation Metrics

The performance of each model was evaluated across four key metrics designed to provide a holistic view of the solution's quality:

- Total Data Downlinked (GB):** The primary mission performance metric.
- Monthly Operational Cost (\$):** The projected recurring cost of the selected network.
- Stations Activated:** The total number of unique ground station locations in the solution, serving as a primary proxy for network complexity.
- Providers Contracted:** The number of unique GSaaS providers required, serving as a secondary proxy for contractual complexity.

### Validation Framework

Our analysis is structured into two distinct pillars, each designed to test a different aspect of the models' performance. To ensure the statistical significance of our findings, each experiment was executed 100 times with randomized system parameters for each trial. The results presented in this paper represent the averaged performance across these trials.

*Pillar 1: Pareto Frontier Analysis*—The objective of this analysis is to demonstrate that the OCP provides a rational, tunable mechanism for navigating the trade-off between network performance and complexity. A 5-satellite constellation was used, and the OCP-Enhanced model was executed across a sweep of  $P_{base}$  values: [\$0, \$100, \$250, \$500, \$1000, \$2500]. The  $P_{base} = \$0$  case is equivalent to the Unconstrained IP Baseline. The resulting data throughput and number of activated stations are plotted to map the efficient frontier, providing a clear visualization of the performance-versus-complexity trade-space.

*Pillar 2: Budget Sensitivity Analysis*—This analysis evaluates the capital efficiency of each model under varying fiscal constraints. A 5-satellite constellation was used as the test case for this pillar. Both the Unconstrained IP Baseline and the OCP-Enhanced model were tasked with maximizing total data throughput, subject to a MaxOperationalCostConstraint. This constraint was systematically varied across three distinct budgetary regimes to simulate different operational postures:

- Resource-Scarce Scenario:** \$150,000/month
- Resource-Adequate Scenario:** \$225,000/month
- Resource-Rich Scenario:** \$300,000/month

This experimental design allows for a direct comparison of each model's resource allocation strategy and performance across a spectrum of realistic operational budgets, stress-testing its ability to efficiently convert capital into data throughput.

### System Parameters

To ensure a direct and robust comparison with prior work, our simulations adopt the comprehensive, randomized cost model proposed by Eddy et al. [1]. This approach tests the models' performance across a spectrum of realistic economic conditions, incorporating one-time capital expenditures and recurring operational costs. Cost parameters for each provider and station were randomly sampled from the uniform distributions summarized in Table 1 for each trial.

A 7-day simulation window ( $T_{sim}$ ) was used to generate contacts, with results projected over a 1-year optimization window ( $T_{opt}$ ). The satellite constellations for each of the 100 trials were generated by randomly sampling from the Celestrak active satellite catalog.

**Table 1.** Randomized Simulation Cost Parameters

Parameter	Value Range (USD)
Integration Cost	Uniform [\$50,000, \$200,000]
Setup Cost	Uniform [\$10,000, \$100,000]
Monthly Cost	Uniform [\$200, \$5,000]
License Cost	Uniform [\$1,000, \$5,000]
Cost per Pass	Uniform [\$25, \$175]
Cost per Minute	Uniform [\$5, \$35]

In addition to costs, performance parameters were also randomized. Ground station data rates were sampled from a uniform distribution of [1.2 Gbps, 2.0 Gbps], while satellite data rates were sampled from [0.9 Gbps, 1.8 Gbps]. The effective data rate for any given contact was taken as the minimum of the two. Furthermore, each station was randomly assigned either a per-pass or a per-minute pricing model with equal probability.

All optimizations were performed on a workstation equipped with a 28-core AMD EPYC 7B13 processor and solved using the Gurobi Optimizer v11.0.3.

## 4. RESULTS AND DISCUSSION

The validation framework was executed to quantitatively assess the performance of the OCP-enhanced model. A summary of the key findings across both experimental pillars is presented in Table 2. The following sections detail the results from each pillar, beginning with the Pareto frontier analysis which forms the core of our contribution.

### Pillar 1: Pareto Frontier Analysis Results

The Pareto Frontier analysis reveals the relationship between network performance (data throughput) and operational complexity (number of activated stations). To isolate this trade-space, the optimization was performed with a non-binding budget cap, representing an effectively unconstrained financial scenario. Figure 1 illustrates the efficient frontier generated by sweeping the  $P_{base}$  parameter across the specified range. The x-axis is inverted, following convention, to represent that a rightward movement corresponds to a reduction in network complexity and thus an increase in operational

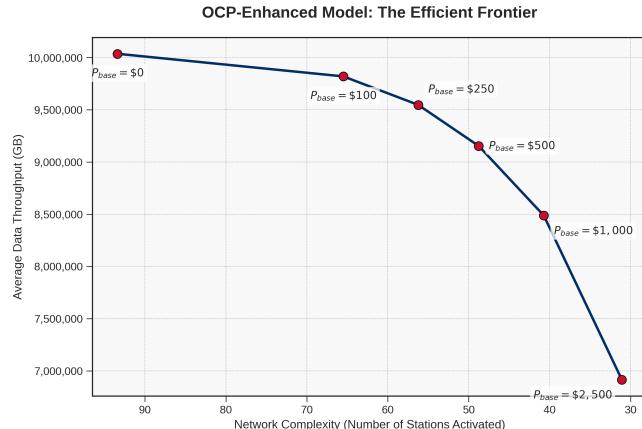
efficiency.

The point at which  $P_{base} = \$0$  serves as the baseline, representing the unconstrained max\_data model. This configuration achieves the theoretical maximum data throughput, averaging approximately 10,050,000 GB over the one-year optimization window. However, this peak performance requires a network of approximately 92 unique ground stations.

The strategic value of the (OCP) is immediately demonstrated by the application of a minimal penalty.

At  $P_{base} = \$100$ , the model recommends a network of 67 stations—a reduction in complexity of over 27%. This significant network consolidation is achieved at the cost of a minor 2.5% reduction in data throughput. This result provides strong evidence that the unconstrained baseline model expends considerable resources activating stations that contribute only marginal data gains, representing an inefficient allocation of capital and operational overhead.

The curve's prominent knee, observed between  $P_{base} = \$250$  and  $P_{base} = \$1,000$ , represents a zone of highly effective, practical trade-offs for a mission operator. Within this region, an operator can achieve substantial efficiencies. For example, at  $P_{base} = \$1,000$ , the network complexity is reduced by over 54% relative to the baseline—slashing the station footprint from 92 to 42—while still securing nearly 85% of the maximum possible data throughput. This demonstrates that the  $P_{base}$  parameter functions as an effective and predictable tuning mechanism, enabling mission planners to precisely calibrate the final network architecture to their specific operational constraints and fiscal realities.



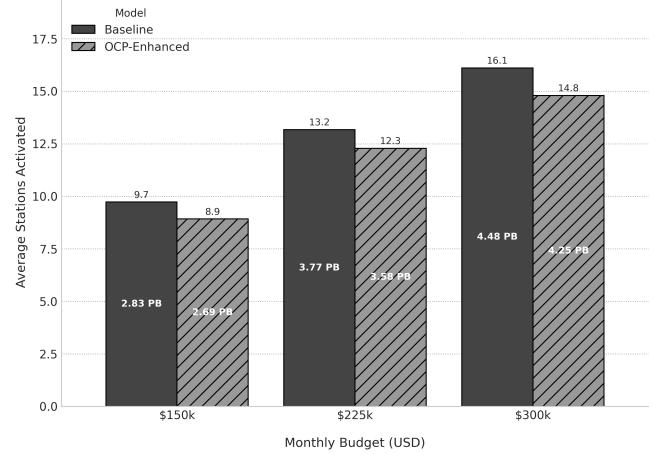
**Figure 1.** The efficient frontier between data throughput and network complexity. The OCP-enhanced model allows operators to significantly reduce the number of required ground stations with minimal impact on performance. The point at  $P_{base} = \$0$  is equivalent to the unconstrained baseline model.

**Table 2.** Quantitative Comparison of Model Performance. The table highlights the superior efficiency of the OCP-Enhanced model in both unconstrained and budget-constrained scenarios.

Scenario	Model	Stns.	Data (GB)	Cost (\$/mo)
Unconstrained	Baseline ( $P_{base} = 0$ )	92.0	10 050 000	1 600 121
Unconstrained	OCP-Enhanced ( $P_{base} = 1000$ )	42.0	8 500 000	1 416 155
\$300k Budget	Baseline	16.1	4 480 000	~300 000
\$300k Budget	OCP-Enhanced	14.8	4 250 000	295 439

**Pillar 2: Budget Sensitivity Analysis**—This analysis evaluates the capital efficiency of each model under realistic fiscal constraints. As shown in Figure 2, both the baseline and OCP-enhanced models were tasked with maximizing data throughput subject to three distinct monthly operational budgets.

Average Model Performance Across Budgetary Constraints



**Figure 2.** Capital Efficiency of the OCP-Enhanced Model Under Budgetary Constraints. The OCP model consistently achieves comparable data throughput with fewer activated stations.

The results demonstrate that the OCP-enhanced model consistently produces more capital-efficient networks across all budgetary regimes. For instance, under a moderately constrained budget of \$300.00/month, the baseline model activates an average of 16.1 stations to achieve a throughput of 4.48 PB. In contrast, the OCP-enhanced model delivers 4.25 PB—nearly 95% of the baseline’s performance—while utilizing only 14.8 stations, an 8% reduction in network complexity. This pattern holds across all scenarios, indicating that even when a hard budget cap forces the baseline model to be selective, the OCP’s intrinsic penalty against complexity enables it to assemble a more consolidated and efficient core network. This confirms that the OCP model provides superior data return per station activated, making it a more effective tool for resource allocation in constrained operational environments.

## 5. CONCLUSION

This paper confronted the critical gap between the theoretical optimality of Integer Programming models for GSaaS procurement and their operational practicality. Standard models, while mathematically sound, often produce fragmented and unmanageable network solutions. To resolve this, we introduced the Operational Complexity Penalty, a regularization term integrated directly into the objective function to penalize network complexity. Crucially, we coupled this with a data-driven normalization method that makes the penalty economically rational and self-calibrating to the specific scenario, eliminating the need for arbitrary parameter tuning.

The results conclusively demonstrate that the OCP-enhanced model generates operationally superior and more efficient ground station networks. The Pareto analysis shows that

mission operators can make explicit, quantitative trade-offs, such as reducing network complexity by over 54% while still securing nearly 85% of the theoretical maximum data throughput. Furthermore, our budget sensitivity analysis confirms the model's capital efficiency, showing it consistently delivers more data per activated station under constrained financial scenarios. This work successfully transforms the ground station selection problem into a practical, strategic planning tool for real-world mission design.

Future work should extend the OCP framework to other mission objectives, such as minimizing the maximum contact gap or total mission cost. Further enhancements could involve more sophisticated penalty functions that account also their geopolitical risk profiles or logistical complexity based on geographic dispersion.

## CODE AVAILABILITY

The source code for the OCP-enhanced model and the experiments presented in this paper is publicly available at: <https://github.com/MaxAurelius/ground-station-optimizer>.

## APPENDICES

### A. VALIDATION OF DATA THROUHPUT

The unconstrained optimization case ( $P_{\text{base}} = \$0$ ) presented in the Pareto Frontier analysis yields a theoretical maximum annual data throughput of approximately  $1.0051 \times 10^7 \text{ GB}$ . This appendix provides a two-part mathematical validation to demonstrate that this result, while aggressive, is physically plausible within the defined system parameters.

#### *Derivation of Required Contact Time*

First, we calculate the required daily performance per satellite needed to achieve the aggregate annual throughput.

- **Total Annual Throughput:**  $1.0051 \times 10^7 \text{ GB}$ .
- **Constellation Size:** 5 satellites
- **Effective System Data Rate:** 1.8 Gbps (maximum)

The required daily data throughput for each satellite is:

$$\frac{1.0051 \times 10^7 \text{ GB}}{5 \text{ satellites} \times 365 \text{ days}} \approx 5507 \text{ GB/day/satellite}$$

To downlink this volume, each satellite requires a total daily contact time calculated as follows:

$$\text{Contact Time} = \frac{5.507 \text{ GB} \times 8 \text{ Gb/GB}}{1.8 \text{ Gbps}} \approx 24.475 \text{ seconds/day}$$

Expressed as a percentage of the total time in a day (86.400 s), the required contact time is:

$$\frac{24.475 \text{ s}}{86.400 \text{ s}} \approx 28.3\%$$

This result indicates that the unconstrained optimization requires each satellite to be in communication with the ground for 28.3% of its total orbit time.

### Comparison Against Orbital Mechanics

Next, we compare this 28.3% requirement against the physical limits of a single LEO satellite pass. We model a representative satellite with the following parameters:

- **Satellite Altitude ( $h$ ):** 550 km
- **Ground Station Min. Elevation ( $el$ ):** 10°
- **Earth's Radius ( $R_e$ ):** 6,371 km
- **Earth's Gravitational Parameter ( $\mu$ ):** 398,600 km<sup>3</sup>/s<sup>2</sup>

The geometry of a satellite pass forms a triangle between the Earth's center (E), the ground station (G), and the satellite (S). Using the Law of Sines, we find the central angle  $\lambda$  swept by the satellite from horizon to zenith:

$$\sin(\eta) = \frac{R_e}{R_e + h} \cos(el)$$

$$\lambda = 90 - el - \eta$$

For our parameters, this yields a total visibility arc of  $2\lambda \approx 29.96^\circ$ .

The orbital period ( $T$ ) for a satellite at this altitude is calculated as:

$$T = 2\pi \sqrt{\frac{(R_e + h)^3}{\mu}} \approx 5730 \text{ s} \quad (\approx 95.5 \text{ minutes})$$

Therefore, the maximum duration of a single, perfect overhead pass is the fraction of the orbit covered by the visibility arc:

$$t_{\text{pass}} = T \times \left( \frac{2\lambda}{360} \right) = 5730 \text{ s} \times \left( \frac{29.96^\circ}{360} \right) \approx 477 \text{ s} \quad (\approx 7.95 \text{ minutes})$$

This single pass covers approximately 8.3% of the satellite's total orbit. The simulation's result of 28.3% aggregate contact time is achieved by the optimizer "stitching together" the equivalent of 3-4 of these ideal passes per orbit, utilizing the extensive 92-station global network. While this represents an extremely high-performance ground segment operating at near-peak theoretical efficiency, the required contact time is well within the bounds of physical possibility.

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## REFERENCES

- [1] D. Eddy, M. Ho, and M. J. Kochenderfer, "Optimal Ground Station Selection for Low-Earth Orbiting Satellites," arXiv preprint arXiv:2410.16282, 2025.
- [2] S. H. Owen and M. S. Daskin, "Strategic Facility Location: A Review," *European Journal of Operational Research*, vol. 111, no. 3, pp. 423–447, 1998.
- [3] N. G. Hall and M. J. Magazine, "Maximizing the value of a space mission," *European Journal of Operational Research*, vol. 78, no. 2, pp. 224–241, 1994.

- [4] G. Corrao, R. Falone, E. Gambi, and S. Spinsante, "Ground Station Activity Planning Through a Multi-Algorithm Optimisation Approach," in *IEEE AESS European Conference on Satellite Telecommunications*, 2012, pp. 1–6.

## BIOGRAPHY



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